ASSESSING THE MULTI-DIRECTIONAL EFFICIENCY ANALYSIS OF GHANAIAN INSURERS IN THE PRESENCE OF UNDESIRABLE OUTPUT

BY

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DECLARATION

I, Debora Afua Antwiwaa Addo, hereby declare that this work is my own, except for the work of others which have been duly cited. This study is the first of its kind submitted to the University of Ghana Business School. To the best of my knowledge, this study has not been presented to any other university for an academic award.

.... 29-09-2022

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CERTIFICATION

I hereby certify that this thesis was supervised in accordance with the procedures laid down by the University of Ghana.

……………………………………… 29th September, 2022

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DEDICATION

This work is dedicated to God for the wisdom, ideas and sound mind to undertake this study. I also dedicate this work to my nuclear family members and eldest cousin, Daniel Boayitey Addo, for the encouragement and support they gave me throughout this study period. I also dedicate it to my friends, Abigail Elorm Bedzra and Charles Zormelo for their unrelenting support.

TABLE OF CONTENT

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LIST OF TABLES

LIST OF FIGURES

LIST OF ACRONYMS AND ABBREVIATIONS

Abbreviation	**Full name**
Activa I	Activa international
AIC	Akaike's Information Criterion
BI	Boone Indicator
BIC	Bayesian Information Criterion
CD	Cross-sectional Dependence
CDH L	CDH Life
CO_2	Carbon Dioxide
CRS	Constant returns to scale
DEA	Data Envelopment Analysis
DMUs	Decision making units
Donewell IC	Donewell Insurance Company
Donewell L	Donewell Life
DVLA	Driver and Vehicle Licensing Authority
DWH	Durbin-Wu-Hausman
Enter L	Enter Life
Enterprise IC	Enterprise Insurance Company Ltd
Equity IC	Equity Insurance Company
FE	Fixed effect
GCC	Gulf Cooperation Council
GFC	Global Financial Crisis
Ghana L	Ghana Life
Ghana UA	Ghana Union Assurance Company Limited
GhanaUnion L	GhanaUnion Life
Glico GI	Glico General Insurance Company Ltd
Glico L	Glico Life
GMM	Generalised method of moments
HHI	Herfindahl Hirschman Index
IAIS	International Association of Insurance Supervisors
JSBs	Joint Stock Banks
L & H	Life and Health

LM	Lagrange Multiplier
LPP	Linear programming program
LSCBBs	Large state-owned commercial banks
MCPT	Multi-criteria production theory
MEA	Multi-directional Efficiency Analysis
Met L	Met Life
Metropolitan IC	Metropolitan Insurance Company Ltd
MID	Motor Insurance Database
MPI	Malmquist productivity index
NIC	National Insurance Commission
NPL	Non-performing loans
NSIA GC	NSIA Ghana Company Ltd
OLS	Ordinary Least Squares
PCBs	Private commercial banks
Phoenix IC	Phoenix Insurance Company
Phoenix L	Phoenix Life
Prime I	Prime Insurance
Provident IC	Provident Insurance Company
Provident L	Provident Life
Quality IC	Quality Insurance Company Ghana Ltd
Quality L	Quality Life
RE	Random effect
ROA	Return on asset
ROE	Return on equity
Regency AI	Regency Alliance Insurance Ghana Ltd
RTS	Return to scale
SBM	Slack-based measure
SCC	Spatial correlation consistent
SCP	Structure-conduct-performance
SFA	Stochastic frontier analysis
SIC	State Insurance Company
SIC IC	SIC Insurance Company Ltd
SIC L	SIC Life

SMCBs	Small-medium commercial banks
SOBs	State Owned Banks
Star AC	Star Assurance Company
Star L	Star Life
TFP	Total Factor Productivity
Unique IC	Unique Insurance Company Ltd
Vanguard AC	Vanguard Assurance Company
Vanguard L	Vanguard Life
VIFs	Variance inflation factors
VRS	Variable return to scale

ABSTRACT

Insurance contributes to a country's economic growth and development. However, despite the plethora of insurance efficiency studies in literature, there are very few insurance efficiency studies in Ghana. Besides, insurance penetration is yet to grow significantly in Ghana, even though various reforms have been enacted to increase insurance penetration and insurance efficiency in Ghana. This study seeks to evaluate the aggregated and disaggregated efficiencies of insurers in Ghana over a sample of 30 insurers from 2008 to 2019, using the non-oriented non-radial multi-directional efficiency analysis and to investigate the impact of competition, leverage, size, solvency, profitability, insurer type and underwriting risk on MEA insurance efficiencies using robust econometric models.

The study data was obtained from the audited financial reports submitted to the NIC.

The results confirmed the distortions in insurance efficiency assessment when undesirable outputs are excluded from insurance efficiency estimation. Among the insurer variables, investment income was identified as the worst performing output variable, reducing the overall performance of insurers. Claims was identified as the best performing variable followed by labour. Among the insurance groups, life insurers were observed to be performing significantly well on its aggregated and disaggregated efficiencies than the non-life insurers. Finally, the previous year's overall performance of insurers and the level of competition were identified as the determinants of MEA insurance efficiency in Ghana.

The inclusion of claims as an undesirable in insurance efficiency assessment enables insurance regulators identify the true efficiency levels of Ghanaian life and non-life insurers.

Key words: claims, insurance, multi-directional efficiency analysis, second-stage analysis, undesirable output.

CHAPTER ONE

INTRODUCTION

1.1 Background study

The insurance and banking sectors contribute positively towards economic growth and development (Han, Li, Moshirian & Tian., 2010; Ibrahim & Alagidede, 2017; Levine, Loayza & Beck, 2000; Pradhan Arvin, Nair, Bennett, & Hall., 2018; Ward & Zurbruegg, 2000). The insurance sector is seen as one of the key components of monetary development as it expands speculations, guarantees legitimate assignment of assets, advances cost decrease through liquidity creation and offers financial assistance to organizations (Chakrabarti & Shankar, 2015; Han et al., 2010; Lee, Chiu & Chang, 2013). Given their importance towards economic growth and development, regulators, policy makers, managers and academic researchers have been looking for ways to determine and improve the efficiency and the dynamic productivity of insurers (Biener, Eling & Wirfs, 2016; National Insurance Commission (NIC), 2018). This has spawned a multiplicity of insurance efficiency and dynamic productivity change studies over the years (Biener et al., 2016; Ho & Hsu, 2021; Kaffash, Azizi, Huang & Zhu, 2020; Lim, Lee & Har, 2020; Ohene-Asare, Asare & Turkson., 2019).

Despite the different reforms enacted by the National Insurance Commission (NIC) Ghana; the separation of insurers into life and non-life, increase in minimum capital requirement (MCR), labour units and innovative products, insurance penetration is yet to grow significantly (NIC, 2010, 2019). Hence, the need to study the performance of Ghanaian insurers. However, such insurance efficiency and dynamic productivity studies in Ghana are limited (Ansah-Adu, Andoh & Abor, 2012; Danquah et al., 2018; Ohene-Asare et al., 2019; Oppong, Pattanayak & Irfan, 2019).

One approach for the efficiency assessment of insurers is Data Envelopment Analysis (DEA). This is a nonparametric linear programming frontier optimization methodology for assessing the relative efficiency of homogenous decision making units (DMUs) that consume multiple distinct inputs to produce multiple outputs (Banker, Charnes & Cooper, 1984; Charnes, Cooper & Rhodes., 1978; Farrell, 1957; Cooper, Seiford & Zhu, 2004) (i.e. CCR and BCC). The method involves the construction of a production or cost or profit frontier from the observed data points using the best-practice organizational entities and measuring the (in) efficiency of a DMU by projecting the observation via the distance in relation to the frontier constructed by the dominating units (Cook & Zhu, 2005; Cooper, Seiford & Zhu, 2011; Cummins, Rubio-Misas & Zi, 2004; Fried, Lovell & Schmidt, 2008; Lozano & Soltani, 2020; Zhu, 2003). The technique then identifies those firms on the frontier as efficient and determines inefficient units, ranks the DMUs, pinpoints potential improvements (i.e. input contractions and output augmentations) and can be used for benchmarking purposes and to assess managerial and regulatory programs or policies etc. (Baležentis & De Witte, 2015; Golany & Yaakov, 1989; Lozano & Soltani, 2020). However, the use of the radial input decreases and output increases to determine a single CCR and BCC aggregated efficiency scores has been criticized as providing partial insights instead of a completely disaggregated (in) efficiency that captures the contribution of individual-specific inputs and outputs (Asmild, Kronborg & Matthews, 2016; Asmild & Matthews, 2012; Baležentis & De Witte, 2015; Kapelko & Lansink, 2017; Tziogkidis, Philippas, Leontitsis & Sickles, 2020). It is argued in this study that, a particular insurer can be doing better in claims than in another input say, labour or another output, say, net premium. Thus, there is the need to be able to select benchmarks such that the non-radial adjustments to the inputs and outputs correspond to the potential improvements identified by considering the individual improvement potential in the variables (Asmild & Matthews, 2012). This is important given the fact that this study first-hand mathematically models claims as an undesirable output. Even though claims were included in some studies as an input (Gaganis, Hasan & Pasiouras, 2013; Rai, 1996; Wu, Yang, Vela & Liang, 2007; Yang, 2006; Yao, Han & Feng, 2007), they are yet to be properly incorporated in the modelling of the behaviour of the insurance firm. This paper first-hand in literature, models claims as an undesirable output using the non-radial non-oriented multi-directional efficiency (MEA) of Bogetoft and Hougaard (1999) and Asmild et al., (2003).

Therefore, the purpose of this study is to evaluate the input-specific and output-specific efficiencies of insurers in Ghana over a sample of 30 insurers from 2008 to 2019, and to pinpoint claims and labour contractions and net premiums and investment income potentials across life and non-life insurers. This will be achieved using the non-oriented, non-radial MEA model. Besides, the study will examine the performance difference(s) between life and non-life insurance groups with their variable-specific efficiencies. Finally, the paper will investigate such insurance-specific factors - competition, size, solvency, leverage, lines of business, profitability and underwriting risk- that may influence the comprehensive efficiency estimates using robust econometric regression methods.

1.2 Problem statement

Despite the increasing number of studies on insurance efficiency (Biener et al., 2016; Biener & Eling, 2012; Cummins, Rubio-Misas & Vencappa, 2017; Eling & Luhnen, 2010; Kaffash et al., 2020; Wise, 2017), there are still some recognised gabs in recent studies. First and foremost, notwithstanding the key contributions the insurance sector makes to a country's economy, none of the insurance efficiency studies has examined the disaggregated view of efficiency estimates via the contributions of individual inputs and/or outputs using the innovative MEA. Existing studies have rather assessed cost or technical or profit efficiency or dynamic productivity (Alhassan &

Biekpe, 2016; Allen & Thanassoulis, 2004; Barros, Nektarios & Assaf, 2010; Diacon, Starkey & O'Brien, 2002; Eling & Luhnen, 2010; Ohene-Asare et al., 2019; Yao et al., 2007). Some of these studies further identified the exogenous determinants of insurance efficiency (Alhassan et al., 2015; Biener et al., 2016; Ohene-Asare et al., 2019; Owusu-Ansah, Dontwi, Seidu, Abudulai & Sebil., 2010). However, the identification of specific input and output variables that contribute to (in)efficiency is important to formulate and assess policy reforms.

Second, the distortions in efficiency scores potentially caused by the exclusion of undesirable outputs in efficiency assessment (Assaf, Matousek & Tsionas, 2013; Atkinson & Dorfman, 2005; Fernández, Koop & Steel, 2002) has resulted in the development of different efficiency techniques for undesirable outputs (Arabi, Munisamy & Emrouznejad, 2015; Chen, Wang & Lai 2017; Dyckhoff & Allen, 2001; Sueyoshi & Goto, 2010; Maghbouli, Amirteimoori & Kordrostami, 2014) as the classical DEA model does not make room for the assessment of undesirable outputs (Färe & Grosskopf, 2004; Seiford & Zhu, 2002). There has been numerous undesirable output efficiency studies in the energy (Apergis et al., 2015; Bi et al., 2014; Mavi & Mavi, 2019; Wang et al., 2015) and the banking sector (Amirteimoori, Kordrostami & Sarparast, 2006; Asmild & Matthews, 2012; Assaf et al., 2013; Lozano, 2016; Seiford & Zhu, 2002). However, a cursory glance at the 132 DEA studies on insurance efficiency examined by Kaffash et al. (2020), the 27 studies by Eling and Luhnen (2010), and the 32 surveyed studies by Cummins and Weiss (2013) reveals that no insurance efficiency study has examined the potential impact of claims as an undesirable output. This could possibly be as a result of the inability of the classical DEA to compute efficiency scores in the presence of undesirable output(s). With the production of undesirable output(s) (Assaf et al., 2013; Sueyoshi & Goto, 2010) being part of insurance services, there is the need for insurance efficiency to be examined by mathematically modelling claims as an undesirable output.

Finally, with MEA being a non-parametric efficiency measure, the existing DEA critics - non statistical and deterministic - as a non-parametric efficiency measure (Schmidt, 1986; Simar & Wilson, 2000, 2007) extends to the novel MEA (Asmild et al., 2019; Asmild & Matthews, 2012; Tziogkidis et al., 2020), non-radial non-parametric efficiency measure. Even though various researchers have suggested alternative approaches to these critics (Banker, 1996; Simar & Wilson, 1998, 2000), several robust econometric regression methods have been adopted in some DEA studies (Ansah-Adu et al., 2012; Barros & Wanke, 2014; Biener et al., 2016; Giantsios & Noulas, 2020; Ohene-Asare et al., 2019). However, to the best of the author's knowledge, only few studies have examined the impact of exogenous covariates on the integrated efficiencies using robust econometric regression models. This calls for the impact of exogenous covariates to be examined on the MEA integrated efficiency of insurers.

1.3 Contributions of the study

From the gaps identified in the problem statements, the study will make contributions to academic literature, policy formulation and insurance practice.

First, the measure of insurance efficiency in the absence of claims as an undesirable output distorts efficiency scores hence its inclusion as an undesirable output will help insurance regulators identify true efficiency levels of Ghanaian life and non-life insurers. In addition, the variable-specific efficiency scores of the life and non-life insurers will enable regulators enact appropriate policies so as to how to increase individual insurance efficiency and country insurance efficiency.

On practice contribution, the study will provide insurance managers with the variable-specific efficiencies of some life and non-life insurers in Ghana. Managers can easily identify specific (in) efficient outputs and inputs to aid variable-specific efficiency analysis.

Finally, the academic contributions come in three folds. This study is the premier insurance efficiency study that mathematically models claims as an undesirable output using the non-radial non-oriented MEA model. Second, it makes an empirical contribution as it uses the non-radial MEA to assess insurance efficiency. Finally, the study identifies the impact of exogenous covariates on integrated insurance efficiencies.

1.4 Research objectives

The main objective of the study is to assess the variable-specific efficiency scores of Ghanaian insurers over the period 2008 to 2019, modelling claims as an undesirable output. The specific objectives are to:

i. Model claims as an undesirable output with the MEA model, and to compare the efficiency estimates between claims as a desirable and as an undesirable output.
ii. Assess the input/output-specific efficiency scores of insurers in a disaggregated view.
iii. Assess the comprehensive and variable-specific efficiency differences between life and non-life insurers.
iv. Investigate those exogenous covariates that affect MEA insurance efficiencies.

1.5 Research questions

The study seeks to answer the following questions:

i. Are there differences between the aggregated and claims-specific efficiency scores of insurers when claims are either used as a desirable or an undesirable output?
ii. What are the input and output-specific efficiency scores of Ghanaian insurers?

iii. Do life insurers outperform non-life insurers in terms of comprehensive and variable-specific efficiencies?

iv. Which insurance-specific factors affect MEA insurance efficiencies?

1.6 Research scope and limitations

This study is focused on life and non-life insurers operating in Ghana. The analysis of this study is based on 13 life and 17 non-life insurers that had been in operation from 2008 to 2019.

This study is limited to insurers whose audited financial reports had been presented to the NIC and had been in operation from 2008 to 2019. Hence, not all Ghanaian life and non-life insurers are used for the study.

1.7 Organisation of the study

The study is divided into five chapters. The first chapter discussed the background of the study, the problem statement, the research objectives and questions, as well as the research scope and some limitations that were encountered during the study. The second chapter reviews and discusses existing articles (conceptually and empirically) in the scope of the study whereas the third chapter discusses into detail the method employed in the study. The fourth chapter is used to present the results of the data analyses. The fifth chapter summarises, concludes and makes recommendations for policy, practice and future academic research.

1.8 Chapter summary

In general, this study seeks to evaluate the input/output-specific efficiencies of Ghanaian insurers over a sample of 30 insurers from 2008 to 2019, and to pinpoint variable potentials across life and non-life insurers in Ghana. The study seeks to help insurance regulators and academic researchers identify the true efficiency levels of Ghanaian insurers in the presence of undesirable outputs (claims).

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This chapter reviews theoretical and empirical literature on insurance efficiency, undesirable outputs and presents an overview of the Ghanaian insurance sector. The overview of the Ghanaian insurance sector discusses the sector's history, recent reforms and the present composition of the sector. The empirical review discusses recent literature on insurance efficiency, undesirable output in the insurance sector and variable-specific efficiency assessment whereas the theoretical review section discusses existing theories that support undesirable output in the production process and variable- specific efficiency analysis.

2.2 Theoretical review

The main theories that support the study are the multi-criteria production theory (MCPT) for the production of undesirable outputs and decision theory for variable-specific efficiency assessment.

2.2.1 Multi-criteria production theory

The MCPT is an extension of the conventional production theories of individual valued added functions. The individual valued added function is defined on relevant input and output variables such that the function transform the input and output variables into different values which are either created or destroyed in the production process (Dyckhoff, 2018). The expansion of the conventional production theories was based on the undeniable contrast between distinct objectives; the input and output variables of a production process objective and the implications of the variables for decision maker's (or an external evaluator's) objective. Whereas the conventional production theories consider these objective to be the same, the MCPT model clearly distinguishes the notion(s) of inputs and outputs. Following Frisch (1965) inputs were defined as things (good and services) which enter the production process, (and sometimes lose their initial identity), and outputs as things (goods and services) which emerge from a transformation process. Dyckhoff (2018) added that the transformation process of inputs into outputs extends to the production of undesirable outputs like waste or emissions.

In the economics sense, production is explained as a process which transforms things with the motive of generating more benefits (positive value created and negative values destroyed) than costs (consume positives and generate negatives). As a results, Dyckhoff (2018) suggests the use of different scales (their own (distinct) natural scale) for the valuation of its variables. This concept of production underpins the addition and formulation of undesirable outputs in efficiency assessment. Employing the non-radial and non-oriented MEA, claims is mathematically modelled as undesirable outputs in the insurance production process.

2.2.2 Decision theory

Decision theory is a theory that guides decisions making (Hansson, 2005). The theory studies the logic and mathematical properties of decision making when the decision maker/agent is uncertain (Fox, 2000). The theory is concerned with goal-oriented behaviour in the presence of options (Hansson, 2005). It is classified into two main classes; the normative decision theory and the descriptive decision theory. The classification of the theory distinguishes how decisions ought to be taken (normative decision theory) from however decisions are taken (descriptive decision theory) (Hansson, 2005).

This theory can be traced back the eighteenth century (Mendoza & Gutleierrex-Pena, 2017). However, in the middle of the 20^{th} century, the theory has developed rapidly through contributions from various academic disciplines (statistics, psychology, mathematics, economics, biology, data science) into an academic field of its own (Mendoza & Gutleierrex-Pena, 2017; Hansson, 1990). Overtime, the theory has received contributions from some newly fields such as jurisprudence, artificial intelligence, optimization, social decision theory and game theory (Hansson, 1991).

The goal of all decision makers (firms, individuals, groups, etc) is to obtain desirable result(s) at the end of the decision-making process. In line with Mendoza and Gutleierrex-Pena (2017), the decision problem of decision makers is defined as an instance where the agent/decision maker is presented with a set of options, $A = \{ a_1, a_2, \dots, a_k\}$ with their associated consequence, $C = \{ c_1, c_2, \dots, c_k\}$ to choose from. Decision makers with prior information with the outcome/consequence of an action will be faced with a decision problem with certainty. However, agents are usually presented with decision problems without uncertainty which is mathematically modelled as:

1. $A = \{ a_1, a_2, \dots, a_k\}$
2. $E = \{ E_{11}, E_{12}, \dots, E_{1m_1;} E_{22}, E_{21}, \dots, E_{2m_2}; \dots; E_{k1;}, E_{k1}, \dots, E_{2m_k}\}$ and
3. $C = \{ c_{11}, c_{12}, \dots, c_{1m_1;} c_{22}, c_{21}, \dots, c_{2m_2}; \dots; c_{k1;}, c_{k1}, \dots, c_{2m_k}\}$

where A are exhaustive and exclusive set of actions; E denotes a set of uncertain events for every action a_i. The collection of events is assumed to be a partition of certain events. C is a set of consequences, where each corresponds to a pair (a_i, E_{ij}) (Mendoza & Gutleierrex-Pena, 2017). In line with Bogetoft and Hougaard (1999), the analogy of an ideal plan embedded in this theory is used as an underlying theory for the (variable-specific) efficiency assessment of Ghanaian insurers.

2.3 Empirical studies

This section reviews some existing efficiency studies in the insurance sector that captured claims as an input or output, including variable-specific efficiency studies in the banking, energy, transport and agricultural sectors. The review comprises the method employed in the study, the study period, sample size and the study's findings.

2.3.1 Insurance efficiency

The insurance market has been incredibly profitable over the years; however, the market is being fraught with several challenges (Kaffash et al., 2020) including premium undercutting, motor insurance fraud and many others (NIC, 2017). This has raised significant interest over their efficiency measurement. This is because the efficiency of insurance firms has been demonstrated to have implications for business failure (Eling & Jia, 2018). The literature appears to be dominated by two efficiency measurement techniques, namely, data envelopment analysis (DEA) and stochastic frontier analysis (SFA) (Eling & Luhnen, 2010; Wise, 2017). It is noteworthy to mention that available literature seems univocal in asserting that there is very little difference in the efficiency scores computed with DEA and SFA (Eling & Luhnen, 2010).

Using DEA and SFA methodologies, Eling and Luhnen (2010) examined the technical and cost efficiency of over 6400 international insurers from 32 countries. They observed that both technical and cost efficiency in the international insurance market experience a steady growth with Denmark and Japan operating the highly efficient insurance markets while the Philippines is the most inefficient insurance market. Interestingly, the authors find evidence that belies the expense preference hypothesis as larger insurers were observed to be more efficient than smaller ones.

Al-Amri, Gattoufi, and Al-Muharrami (2012) examined the technical efficiency of insurance firms in the GCC regional market. Using DEA methodology on 32 insurers over the period 2005 to 2007, they found that the GCC insurance market is moderately efficient. Similarly, the efficiency performance of the Indian health insurance industry has been found to be operating suboptimal in terms of technical efficiency with just 30% efficient health insurers (Siddiqui, 2021). Additionally, it was noted that stand-alone health insurers had superior level of technical efficiency compared to health insurance division under general insurers, supporting the strategic focus hypothesis against the conglomeration hypothesis.

Cummins and Weiss (2013) developed the stochastic frontier analysis and the non-parametric frontier analysis to analyse firm performance. The study identified seventy-four (74) insurance efficiency studies over the period, 1983 to 2011. Over half of these studies published in top tier journals thus were reviewed intensively. It was observed that about 60% of the identified studies used DEA for its analysis. Furthermore, the value-added approach was identified to be commonly used approach for measuring outputs. The corporate reporting practices across countries greatly influenced the input choices in the identified studies.

Recently, Kaffash et al. (2020) considered the increasing interest in the use of DEA for efficiency assessment and undertook a comprehensive insurance efficiency survey of published insurance efficiency studies that applied DEA from 1993 to July 2018. The survey built upon the comprehensive work of Cummins and Weiss (2013), combining DEA application to its methodologies. Of the 132 DEA applications studies sampled 42% were published between 2010 and 2016, which recorded the highest DEA applications in the insurance sector. The authors focused on the analysis of the input/output variables used, their selection period, orientation, type of insurer, geographical distribution and application of DEA models. The findings suggest that the impact of recent changes in insurance industries - InsurTechs, market transparency and micro-insurance - on efficiency has not been explored. In addition, unlike other financial industries whereby DEA with the presence of undesirable factors have been assessed, the findings point out that no study has yet used DEA under such conditions. Further findings suggest that newly developed DEA approaches like modified directional distance function, satisficing DEA and fuzzy DEA recorded few applications in insurance efficiency.

Despite the extant literary on insurance efficiency in DEA, no study has yet assessed the variable-specific efficiency analysis for the insurance market and no insurance study has assessed efficiency with MEA in the presence of its undesirable factors. There is therefore the need for the assessment of the variable-specific efficiency scores of insurers, in addition with the assessment of insurer efficiency in the presence of undesirable output.

2.3.2 Variable-specific efficiency

The MEA approach developed and operationalized by Bogetoft and Hougaard (1999) and Asmild et al. (2003) respectively, was further elaborated by Bogetoft and Hougaard (2004), Asmild and Pastor (2010), Asmild et al. (2016) and Baležentis and De Witte (2015), has been applied in different contexts, such as in the works of Holvad, Hougaard, Kronborg, and Kvist (2004), Asmild and Matthews (2012) and Wang, Wei, and Zhang (2013). Notably, it observed that when undesirable outputs are omitted, efficiency scores become distorted. Equally, in view of disaggregate ion of efficiency scores by MEA, several researchers use the novel MEA to assess firm-level variable-specific efficiency scores in the banking sector (Asmild et al., 2016; Asmild & Matthews, 2012; Tziogkidis et al., 2020), transportation sector (Bi, Wang, Yang, & Liang, 2014; Holvad et al., 2004), agricultural sector (Asmild et al., 2016; Manevska-Tasevska, Hansson, Asmild, & Surry, 2018, 2021), and energy and environmental sectors (Wang et al., 2013; Wang, Yu, Li, & Wei, 2015) in order to assess variable-specific efficiency scores of its inputs and/or outputs, in addition with undesirable outputs.

Asmild et al. (2019) applied the novel MEA to measure the patterns and differences in inefficiency scores between Islamic and non-Islamic banks focusing on the period that marked the impact of global financial crisis in Bangladesh. The study sampled 30 private commercial banks (PCBs) which comprised 1st, 2nd and 3rd generation conventional banks, as well as Islamic banks over the period 2001-2015. Using labour costs and other costs as inputs and off-balance-sheet earnings and balance-sheet earnings as outputs, the authors assumed a constant return to scale (CRS) under the non-oriented MEA model. The following results were established. First, there is no observed significant differences in the inefficiency patterns between Islamic and non-Islamic banks for the period outside the depth of the Global Financial Crisis (GFC). Additionally, there was significantly higher efficiencies of both inputs including one of the outputs in the time window of the GFC period for the Islamic banks compared to the private conventional banks.

Asmild et al. (2016) researching on managerial and program efficiency in family firms used the novel MEA approach to estimate efficiency. Thus, the authors focus on estimation of input-specific efficiencies, which provides further understanding into the underlying efficiency differences that may exist between farm types. The results show that there is a clear difference between the efficiency scores on the different inputs as well as between the farm types of crop, livestock and mixed farms, respectively. Crop farms have the highest program efficiency, but the lowest managerial efficiency, and that the mixed farms have the lowest program efficiency.

A number of researchers have used MEA to investigate the variable-specific efficiency scores of banks in the Chinese banking sector (Asmild et al., 2019; Asmild & Matthews, 2012; Tziogkidis et al., 2020). Zhu et al. 2020, a recent MEA application to the Chinese banking sector applies the novel Malmquist productivity index (MPI) of MEA to investigate the overall total factor productivity growth as well as the variable specific productivity growth of Chinese banks. The study incorporates the MEA-based MPI into the meta-frontier framework considering the heterogenous environment in the Chinese banking sector. 16 main Chinese banks over the period 2005 - 2015 are sample for the study - 176 observations. The banks are divided into two main groups namely large state-owned commercial banks (LSCBBs) and small-medium commercial banks (SMCBs) and considered to have interest expenses and non-interest earnings as its inputs, interest income and non-interest income as its desirable outputs and non-performing loans as its undesirable outputs. They compared the novel MEA-MPI with the conventional DEA-MPI and found a negative overall Total Factor Productivity (TFP) growth, with non-performing loans (NPL) and non-interest income being the main sources impacting TFP growth in the country's banking sector. They further observe the gap of productivity change between LSCBs and SMCBs to be narrowing and identify technological change to be the main gap between banks. Over, all they assert that the conventional MPI probably overestimates TFP growth.

In general, it is observed that there exists no insurance efficiency study that has assessed the variable-specific efficiency of its inputs/outputs. The variable-specific assessment of firms and industries is necessary to effectively assess the impact of enacted reforms in the industry or firm.

2.3.3 Variable-specific efficiency and undesirable output

Over the years, various techniques have been developed to measure efficiency performance in the presence of undesirable outputs (Arabi et al., 2015; Chen et al., 2017; Dyckhoff & Allen, 2001; Sueyoshi & Goto, 2010; Maghbouli et al., 2014) due to the inability of the traditional DEA to compute efficiency scores in the presence of undesirable variables (Färe & Grosskopf, 2004; Seiford & Zhu, 2002). These models include DEA directional distance function (DDF) and slack based DEA (Tone, 2001). However, due to the variable-specific nature of the novel MEA and the freedom to use negative inputs and outputs (Bogetoft & Hougaard, 1999), much attention is being given to the model for the assessment of variable-specific efficiencies in the presence of undesirable outcomes (Asmild & Matthews, 2012, Zhu et al., 2019).

Asmild and Matthews (2012) is the first study that used MEA to assess the efficiency performance of Chinese banks while capturing one of its output variables as an undesirable output, non-performing loans. The study delved deeper into one of the popular findings of most Chinese banking sector studies - "State Owned Banks (SOBs) are less technically efficient than Joint Stock Banks (JSBs) and the JSBs have improved their position in the run up to the opening up of the banking sector." The patterns and levels of efficiencies of these two banks were assessed, sampling 14 banks from 1997 through to 2008. The reforms enacted about two decades ago in the China Banking Regulatory Commission guided the study. Following Thanassoulis, Portela and Despic, (2008), non-performing loans, an undesirable output was used as an input in addition with three other inputs namely labour, fixed assets and bank deposits. The inputs were further classified into two groups; discretionary inputs (labour and non-performing loans) and non-discretionary inputs (fixed assets and deposits) while the study outputs were net interest earnings and non-interest earnings. The findings of the study are in contrast with the popular findings, the JSBs are more efficient than the SOBs. The study confirmed one of its hypotheses on the differences in the efficiency patterns in the two types of banks.

Zhu et al. (2019) uses an improved MEA approach to evaluate the energy efficiency while considering the slack problem of production. The study focuses on 30 Chinese provinces and three major economic regions as it assesses the energy variable-specific efficiency in addition with the carbon emissions variable specific efficiencies. Both the improvement paths and improvement potential for energy efficiency of these provinces were assessed in the study and in line with Asmild and Matthews (2012), Zhu et al. (2019) used the SBM model aggregation idea of Tone (2001) but develops a more comprehensive MEA overall efficiency model which captures all the variables in the study. The findings reveal that the country's provincial energy is olived-shaped with significant spatial imbalance. In addition, it reveals a large potential value for CO_2 emission in the Central region with a relatively large energy saving potential for the two other regions, Western and Eastern.

Wang et al. (2015) attempted to understand regional environmental efficiency differences in China using the novel MEA approach. They evaluated the environmental efficiency of industrial sectors in major Chinese cities considering the period 2006 - 2010. Thirty (30) capital cities of China's provinces were sampled using three inputs, one desirable output and five undesirable outputs for in the study. The findings recommended that specific attention be given to different industrial pollutants in the various capital cities. In addition, the study identified the beginning of the alleviation of the inequitable nationwide industrial developments of China's cities.

In another study, Bi et al. (2014) aimed at gaining deeper insight into the regional energy and environmental efficiency of the Chinese transportation sector. The authors adopted the modified MEA model to investigate the levels and patterns of efficiency. Unlike previous studies on China's transportation sector, $C0_2$ emission was chosen as an undesirable output in the study. Thirty (30) provinces in mainland for the period 2006-2010 were sampled. Labour and capital were nonenergy inputs; volume of energy consumed in the transportation sector represented energy input and value-added amount and volume of CO_2 emissions denoted outputs. The overall comprehensive

MEA efficiency for each region, the variable-specific efficiencies for energy and CO_2 emission as well the reduction potential for energy and CO_2 emission are all assessed. The results showed that not many regions were efficient during the study period. Greater chances of reducing CO_2 emission and energy consumption were also identified.

In short, the above discussion gives credence to the wide acceptance of the novel MEA approach in modelling efficiency differences instead of the traditional DEA approach. Specifically, the available empirical evidence demonstrates that additional insights can be gained with the novel MEA approach compared to traditional DEA (Asmild et al., 2016). Interestingly, as far as we have reviewed, there is no variable specific study in the insurance industry. We fill this gap in the literature and model the variable-specific efficiency scores of Ghanaian insurers using claims as an undesirable output in the novel MEA framework.

2.3.4 Undesirable output in the insurance sector

The production of undesirable outputs from the agricultural, energy and manufacturing sectors have received much attention from environmental policy makers (Fernández et al., 2002; Khan et al., 2018; You & Yan, 2011). Several studies have been carried out to effectively assess their performance while considering the production of these undesirable outputs (Bi et al., 2014; Dyckhoff & Allen, 2001; Fernández et al., 2002; Khan et al., 2018; You & Yan, 2011; Zhu et al., 2019). Furthermore, comprehensive efficiency models have been developed to effectively assess these firms (Khan et al., 2018; You & Yan, 2011). Unlike the bad outputs of the these sectors which affect the environment (Dyckhoff & Allen, 2001; You & Yan, 2011), those of financial firms – claims and non-performing loans - adversely affect the firm. Studies have been carried out in the banking sector which have considered non-performing loans as an undesirable output (Assaf et al., 2013; Bi et al., 2014). However, no much studies have considered claims as an undesirable output in insurance efficiency assessment (Owusu-Ansah et al., 2010). Some studies who came close to this captured claims as an input (Rai, 1996; Yuengert, 1993) following the efficiency basis; minimize inputs and maximise outputs (Charnes et al., 1978).

Yang (2006) introduced a new two-stage DEA model which assessed systematic efficiency for the Canadian Life and Health (L & H) insurance industry. The model incorporated the production and investment performances of insurers. To assess production efficiency, labour expenses, general operating expenses, capital equity and claims incurred were chosen as inputs. For this study, the production approach considered insurers to be providers of products and services while undertaking its sole responsibility, risk reduction through pooling. The results of the study demonstrated that the Canadian L & H insurance industry operated fairly during the period under study,1998. The scale efficiency for this insurance industry was also identified.

Wu et al. (2007) is another study on the Canadian Life and Health insurance industry. They developed a problem-oriented DEA model which is able to simultaneously assess the production and investment performance of insurers in the Canadian Life and Health insurance industry while considering the interaction that often occurs between the indicators characterizing the two aspects of performance; production and investment. In line with Yang (2006), the inputs chosen for the assessment of production performance included labour expenses, general operating expenses, capital equity and claims incurred with net actuarial reserves, investment expenses, total investments, and total segregated funds were considered as inputs for the investment performance assessment. Again following Yang (2006), claims was used as an input in the production approach because it is appropriate for assessing insurers' ability to satisfy the claims of its insureds. The results of the study confirmed Yang (2006) findings, the Canadian life and health insurers operated efficiently during the three-year period under study; 1996 – 1998. However, Wu et al., (2007) identified no scale efficiency in the industry.

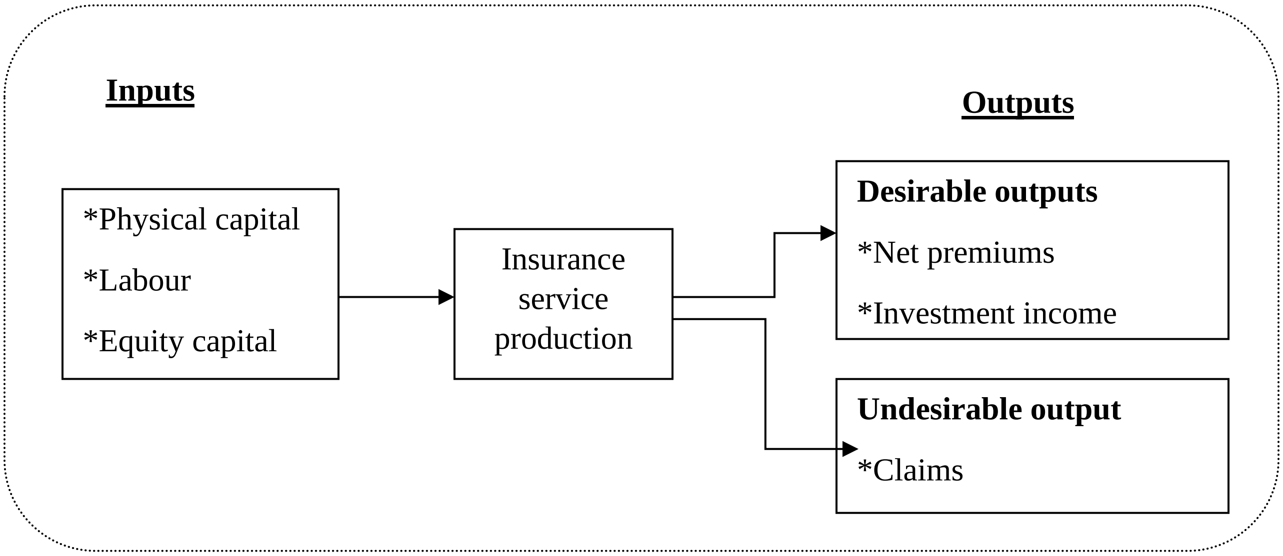
In an insurance efficiency study that investigated whether capital market considers efficiency of insurers, 399 listed insurance firms from 52 countries were sampled for the period 2002 through to 2008 (Gaganis et al., 2013). The study used stochastic frontier analysis to assess the profit efficiency and controlled for country-specific characteristics. Claims was used as an input variable following Rai (1996) - claims form an integral and importance part of the annual expenses of insurer thus must be captured as an input - and the purpose of the study, stockholders like their firms to minimize expenses while maximizing their returns. The efficiency scores were regressed with the stock returns, a positive and statistically significant relationship was identified between the current and past profit efficiency changes and market adjusted stock returns.

The improper definition of variables during efficiency assessment results to distorted and inappropriate conclusions. There is the need for an insurance efficiency study to properly define its variables, making room for undesirable outcomes as these outcomes cannot be omitted from the provision of its services. This study captures claims as an undesirable output.

Appendix A presents a tabular taxonomy of previous variable-specific studies.

2.4 Conceptual Framework

Figure 2.1 presents the conceptual framework that explains the study pictorially. It follows from the empirical and theoretical reviews the presence of an undesirable output in the provision of insurance services and the relationship between the input and (desired and undesirable) output variables.



Source: Author's own construct, 2021

Figure 2.1 Conceptual framework of the relationship between first stage variables.

2.5 Frontier efficiency

The modern efficiency and dynamic productivity of decision-making units (DMUs) began with the collective works of Farrell (1957), Debreu (1951), Koopmans (1951) and Seiford and Thrall (1990). In the production framework, efficiency is defined as the comparison of the observed output with the maximum potential output obtainable from the input, or the observed input with the minimum potential input demanded to produce the output or a blend of the two (Farrell, 1957; Fried et al., 2008; Lovell, 1993). This definition explains technical efficiency which can be input reduction (input-conservation), outputs augmentation (output-expansion) or both (non-orientation) (Fried et al., 2008). In summary, the assessment of efficiency and productivity change demands the initial identification of an efficiency frontier formed with best practice firms. The assessment can be undertaken using parametric (econometric approach) or non-parametric (mathematical programming approach) models (Coelli et al., 2005; Daraio et al., 2020; Fried et al., 2008; Lampe & Hilgers, 2015).

DEA is a non-parametric linear programming frontier optimization method of assessing the relative efficiency of homogenous decision making units (DMUs) that consume multiple distinct inputs to produce multiple outputs (Banker et al., 1984; Charnes et al., 1978; Farrell, 1957; Cooper et al., 2004) (i.e. CCR and BCC). The method involves the construction of a production or cost or profit frontier from the observed data points using the best-practice organisational entities and measuring the (in) efficiency of a DMU by projecting the observation via the distance in relation to the frontier constructed by the dominating units (Cook & Zhu, 2005; Cooper et al., 2011; Emrouznejad & Yang, 2018; Fried et al., 2008; Lozano & Soltani, 2020). Under this non-parametric efficiency assessment technique, DMUs on the frontier are identified as efficient whereas DMUs outside the frontier are classified as inefficient units (Baležentis & De Witte, 2015; Golany & Yaakov, 1989; Lozano & Soltani, 2020). Instead of a completely disaggregated (in) efficiency that captures the contribution of individual-specific inputs and outputs, DEA uses the radial input decreases and output increases to determine single CCR and BCC aggregated efficiency scores (Asmild et al., 2016; Asmild & Matthews, 2012; Baležentis & De Witte, 2015; Tziogkidis et al., 2020).

Multi-directional efficiency analysis (MEA) is a DEA modification which separates the issue of benchmark selection from the issue of efficiency measurement (Bogetoft & Hougaard, 1999; Kapelko & Lansink, 2017; Labajova et al., 2016). The model was postulated by Bogetoft and Hougaard (1999) who provided an axiomatic foundation which supports the implicit benchmark selection over the potential improvement selection approach. Asmild et al. (2003) further operationalised the potential improvement approach with DEA and proposed the name, multi-directional efficiency analysis (MEA). The model consists of two stages; ideal reference point identification, which is the first stage and improvement potential point selection for each input/output variable which is the second stage (Asmild et al., 2003; Asmild & Matthews, 2012).

Unlike DEA, the selection of input reduction and output expansion benchmarks for MEA are based on the specified improvement potential related to each input and output separately (Asmild et al., 2003; Asmild, Baležentis, Hougaard, 2016). In an MEA input-oriented analysis, the largest reduction potentials for each input are identified and combined with the minimum possible input usage in each dimension to identify the ideal reference point (Asmild et al., 2003; Asmild & Pastor, 2010). The difference between the unit under analysis and the ideal reference point is used to find the directional vector of each unit (Asmild & Pastor, 2010). Bogetoft and Hougaard (1999) and Asmild et al. (2003) have discussed some desirable properties of the MEA model over the traditional DEA. First, unlike DEA which selects both weakly and strongly efficient benchmarks, MEA selects only strongly efficient benchmarks. Second, because of its non-radial improvement approach, MEA explicitly recognises improvement potentials between input and output dimensions. Third, MEA can be extended to estimate efficiency under input orientation, output orientation and non-orientation (input reduction and output augmentation simultaneously). Fourth, MEA can be extended to include discretionary and non-discretionary variables simultaneously. Finally, MEA can be run under both the constant return to scale and variable return to scale (VRS) technology, it is invariant to affine transformation under the VRS technology.

2.6 Overview of the Ghanaian insurance sector

The commencement of the Ghanaian insurance is traced to 1924, a colonial era, where the Ghanaian insurance industry was populated with oversea insurers which had their head offices situated in the United Kingdom and elsewhere. As a result, they appointed foreign trading companies to act as chief agents in other countries including the then Gold Coast. However, the policies these insurers designed were limited to only the British nationals residing in the countries with the chief agents. Royal Exchange Assurance Corporation was the first of such insurance companies to operate in the Gold Coast and was represented by Barclays Bank, its chief agent, in 1924. Other foreign companies followed suit after Royal Exchange Assurance Corporation which is now Enterprise Insurance Company and opened offices in the Gold Coast.

In 1955, the first local insurance company, Gold Coast Insurance Company, was established in the Gold Coast. It provided life assurance policies to its citizens and other Africans that were residing in the country since the foreign insurers were only insuring the Europeans. After the attainment of the country's independence in 1957, its name was changed to Ghana Insurance Company. In 1958, another local insurance company was established to mainly underwrite fire and motor insurance businesses in the country, the Ghana General Insurance Company. Four years after its operation, it was merged with two other local insurers including the first local insurance company and the Co-operative Insurance Company, to form the State Insurance Corporation (SIC). SIC was incorporated by an Executive Instrument, EI 17. Some laws were passed after its formation which made it monopolistic over all government businesses. Over time, huge sums of monies were paid to foreign reinsurers for reinsurance, as result, legislation laws were passed in 1972 one of which was used to establish Ghana Reinsurance Organization (GRO). Moving forward, other insurance legislations were passed which compelled the foreign insurers to withdraw out of the Ghanaian insurance market.

The NIC is the mandated supervisory body for Ghana's insurance sector. According to the Insurance Act 2006, (ACT 724), NIC is mandated to ensure effective administration, supervision, regulation and control over the insurance businesses in Ghana (NIC, 2019). It is responsible for the approval of both premium and commission rates, provision of bureau for complaints resolution, enforcement of compliance as well as public education of the Ghanaian citizens. The sector is governed by the Insurance Act 2006, ACT 724 which complies with the International Association of Insurance Supervisors (IAIS) core principles.

Before Insurance Act 2006 was enacted, NIC was operating under the Insurance Act 1989, (PNDC Law 227). Insurance companies were operating as composite insurers until a new law demanded that general insurance businesses be separated from life insurance businesses. The present Insurance Act requires that insurers operate life businesses and non-life businesses separately. Thus, currently, the sector comprises 20 life insurers, 29 non-life insurers, 3 reinsurers, 93 broking companies and one reinsurance contact office (NIC, 2019).

2.7 Industry challenges and reforms

The Ghanaian insurance industry has experienced rapid premium growth over the years since its inception however, the industry is being faced with overarching challenges which are inhibiting the increase of its penetration and efficiency. The NIC Board which was sworn in on 18th August, 2017 started operation by comprehensively addressing the challenges impeding the industry's growth, profitability and efficiency. The overarching challenges of the industry include low trust from the insuring public, many small inefficient loss-making players, proliferation of fraudulent motor insurance stickers on commercial vehicles, loss of huge investments held by poorly managed micro finance institutions and banks (NIC, 2017). The Chairman of the existing Board, Mr. Emmanuel Ray Ankrah, reported that the Board has developed a four-year strategic plan with the sole aim of the industry excelling its mandate as stated in the Insurance Act, 2006 (Act 724). The strategic plans seek to address the industry's supply and demand constraints, which consists of construction and implementation of an Electronic Motor Insurance Database (MID), passage of a new Insurance Bill, insurance cover for projects funded by Donors and Development partners, compulsory fire insurance for public places, revamp of agricultural and marine insurance, effective consumer education, development of annuities market, improvement of claims management and many others.

In 2019, the existing NIC board constructed and implemented an Electronic MID to be used to store information on all motor insurance policies, making an interface available to Driver and Vehicle Licensing Authority (DVLA) (NIC, 2018). This initiative is to help reduce the proliferation of fake motor insurance stickers while reducing the number of uninsured motor vehicles on the roads. The implementation and construction of an Electronic MID is one of the key initiatives of the current NIC board, to curb one of the overarching challenges facing the industry (NIC, 2018).

Passage of a new Insurance Bill into an Act is another initiative developed by the Board to address the sector's challenges. The chairman reported that the passage of the Bill into an Act will consequently improves the industry's weak segments – marine and agricultural insurance, compulsory group life and public liability insurance – and protect its policyholders and stakeholders. He explained that, with Ghana being an import dependent country and agriculture being the country's biggest employer and highest contributor to GDP, calls for the revamp of the insurance terms on goods imported from the country.

Furthermore, the NIC board passed an Insurance Bill which outlined a strategic objective of improving the industry's supervisory effectiveness (NIC, 2018). Included in this main strategic objective were the review of the Minimum Capital Requirements for insurers to ensure the existence and operation of adequately capitalized insurers, the design and implementation of a Market Conduct Supervisory framework to ensure fair and transparency of policyholders, development of a Risk Based Supervisory framework which will issue Supervisory Risk Ratings to each insurer and the implementation of Risk Based Capital framework which links the risks and nature of business with the player's capital requirement. The board suggests that the implementation of all these reforms coupled with the cooperation of the stakeholders in the insurance industry will improve the industry's growth, profitability and efficiency.

2.8 Chapter summary

This chapter reviewed related theories that supports the study. First, the multi-criteria production theory supports the use of claims as an undesirable output in the insurance industry. Second, the decision theory supports the variable-specific efficiency analysis of insurers.

Empirical studies on insurance efficiency, variable-specific efficiency analysis with and without undesirable outputs and undesirable outputs in the insurance sector were all reviewed in this chapter.

CHAPTER THREE

METHODOLOGY

3.1 Introduction

This chapter discusses the concept of efficiency and explains the methods employed in the study. The novel non-parametric efficiency measure, MEA, postulated by Bogetoft and Hougaard (1999) and subsequently operationalised by Asmild et al. (2003), is used to assess the variable-specific efficiency scores of Ghanaian insurers from 2008 to 2019. Robust econometric regression techniques such as the two-step systems Generalised Method of Moment (GMM) are used to examine the impact of exogenous variables – competition, size, solvency, profitability, leverage and type of insurer – on the MEA efficiency scores. R version 4.0.5 is used to generate the descriptive statistics, assess the variable-specific efficiency scores and compute the regression results for the second stage analysis.

3.2 Research design

Research design is a vital research framework that connects the gap between the research questions and the research process (Blanche et al., 2006). It plays a key role in the selection process of the research approach, research method(s) and paradigm(s) (Creswell & Creswell, 2018). Irrespective of the rigour used in a statistical analysis, the conclusion of a research may be useless if the research design is not appropriate for the study (Hancock et al., 2010). This confirms the assertion by Miles and Huberman (1994); the choice of a research design constrains and supports the ultimate conclusions of a study. Among the three well-known research approaches; quantitative, qualitative and mixed method (Creswell & Creswell, 2018), the quantitative approach is used because it allows researchers to objectively examine the relationship between input and output variables of insurers and to assess their contribution to the insurer's efficiency.

Paradigms are broadly seen as worldviews. Guba (1990) posits that "worldviews are a basic set of beliefs that guides action" (p.17), that is, a researcher's belief greatly influences the action(s) employed in research. However, Morgan (2007), suggests that paradigms are not only limited to the things people think about and believe but extend to the thoughts people have about the nature of research; what worldviews consist of. Among the existing research paradigms, the positivist worldview is employed. This paradigm believes in the existence of reality, such that this reality is driven by immutable laws of nature and mechanisms (Guba, 1990). The positivist worldview is adopted because the assessment of the variable-efficiency scores requires the development of numeric measures for insurers which call for objective views rather than subjective views.

3.3 Data, sampling and sources

Ghana's insurance sector presently consists of 20 life and 29 non-life insurers (NIC, 2019). Following the separation of the composite insurers into life and non-life groups in December, 2006, the study sampled both life and non-life insurers to assess both group and individual comprehensive and variable-specific efficiency differences. Hence, 13 life and 17 non-life insurers that had been in operation from 2008 to 2019 were sample for study. The study data was retrieved from the statement of financial position and comprehensive income of the audited annual reports of the sampled insurers. These reports were collected from the National Insurance Commission (NIC). NIC is the regulatory body whose responsibility is to "ensure effective administration, supervision, regulation and control the business of insurance in Ghana" (NIC, 2019). It is mandatory for all life and non-life insurers operating in Ghana to present their audited annual financial report to the NIC. This makes the NIC the most reliable source of data for this study. Despite the law guiding the submission of audited annual reports, the audited annual reports for some insurers were not obtained from the NIC nor were information on their financials found in the NIC annual reports. Following Cummins and Xie (2013) and Eling and Schaper (2017), figures that were not found were mathematically generated (linearly interpolation) in R, hence a balanced data panel is used for this study. NIC has been the data source for several Ghanaian insurance efficiency studies including Owusu-Ansah et al. (2010), Alhassan et al. (2015), Ohene-Asare et al. (2019), Alhassan and Biekpe (2016) and Danquah et al. (2018). The study period for these studies varies from three years to ten years, however, this study considers a twelve-year study period.

3.4 Formulating the multi-directional efficiency analysis

The study considers a production technology that uses a vector of input X to produce vectors of output Y (desirable) and C (undesirable). The production technology is defined as:

$$L = \{(X, Y, C) \text{ produce } (Y, C)\} \tag{3.1}$$

The production technology L considered undesirable outputs as by-products since they are produced with desirable outputs (Färe & Grosskopf, 2004; Bi et al., 2014). Three assumptions of joint production technology are imposed on the production technology in equation (3.1) for the asymmetric treatment of the desired and undesired outputs (Bi et al., 2014; Färe et al., 2005; Reyna & Fuentes, 2018). The three assumptions are as follows:

i. Strong or free disposability of desirable outputs:

   If $(X, Y, C) \in L$ and $Y^* \leq Y$, then $(X, Y^*, C) \in T$. This assumption is the same traditional assumption handling the disposability of desirable outputs. The axiom states that any output vector with a smaller desirable output is feasible if the observed desirable and undesirable outputs vectors are possible (feasible). This assumption guides the free disposability of desirable outputs without any cost (Färe et al., 2005; Färe & Grosskopf, 2004).

ii. Weak disposability of undesirable outputs (Shephard, 1970) :

If $\{(X, Y, C) \in L$ and $0 \leq \theta \leq 1$, then $(X, \theta Y, \theta C) \in T\}$. Weak disposability means that the proportional contraction of desirable and undesirable outputs is possible, hence for any given input, bad outputs can be reduced if and only if good inputs are also reduced in proportion. This axiom suggests that undesirable outputs cannot be freely disposed off, hence the sole reduction of undesirable outputs is impossible, due to their costly disposal which affects desirable outputs (Färe et al., 2005; Färe & Grosskopf, 2004; Reyna & Fuentes, 2018).

iii. Desirable and undesirable outputs being null-joint (Shephard, Ronald & Fare, 1944):

If $\{(X, Y, C) \in L$ and $C = 0$, then $Y = 0\}$. This assumption implies that undesirable outputs are by-products of desirable outputs, hence the production of desirable outputs cannot be separated from the production of undesirable outputs. Relating the assumption to the insurance environment, the coverage of a risk is linked with the occurrence of a covered loss which usually demands claim payment - as desirable outputs are being produced, undesirable outputs will be produced alongside (Färe et al., 2005; Reyna & Fuentes, 2018).

From axiom (a) and (b), strong disposability of desirable output vector implies weak disposability of both desirable and undesirable outputs. With the imposition of these assumptions, production technology L is an insurance production technology. A set of insurance firms $(j = 1, \ldots, n)$ are considered to produce s_1 desirable outputs $(r = 1, \dots, s_1)$ and s_2 undesirable outputs $(k = 1, \dots, s_2)$ with m inputs $(i = 1, \dots, m)$. Consistent with Bi et al. (2014), the insurance production technology L is modelled for a DEA framework as:

$$L = \left\{ (X, Y, C) : \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ij}, \quad i = 1,2, \dots, m, \sum_{j=1}^{n} \lambda_j y_{rj} \leq y_{rj}, r = 1, 2, \dots, s_1 \right. \\ \left. \sum_{j=1}^{n} \lambda_j c_{kj} = c_{kj}, \qquad k = 1, 2, \dots, s_1 \right\} \tag{3.2}$$

λ_j in equations (3.2) represents the weights of the variables $(\sum_{j=1}^{n} \lambda_j = 1,\ \lambda_j \geq 0)$. The strong or free disposability of the desired outputs and the weak disposability of the undesirable outputs are imposable as a result of the equality and inequality on the undesirable outputs and desirable outputs respectively. A Multi-directional Efficiency Analysis model is formalised following Asmild and Matthews (2012) and Zhu et al. (2019). (x_{i0}, y_{r0}, c_{k0}) is chosen as the production plan for DMU_0. For each input, desirable output and undesirable output variable, an ideal reference point is obtained by solving the three linear programming problems (LPP)

$$\min d_{i0}$$

$$\text{subject to} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq d_{i0}, \\ \sum_{j=1}^{n} \lambda_j x_{-ij} \leq x_{-i0}, \ \text{-}i = 1, \dots, i-1, i+1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, \ \ \mathrm{r} = 1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{k0}, \ \mathrm{k} = 1, \dots, s_2 \\ \lambda_j \geq 0, j = 1, \dots, n \end{cases} \tag{3.3}$$

$$\max \delta_{r0}$$

$$\text{subject to} \begin{cases} \sum_{j=1}^{n} \lambda_j y_{rj} \geq \delta_{r0}, \\ \sum_{j=1}^{n} \lambda_j y_{-rj} \geq y_{-r0}, -r = 1, \dots, r-1, r+1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, \dots m \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{k0}, k = 1, \dots s_2 \\ \lambda_j \geq 0, j = 1, \dots, n \end{cases} \tag{3.4}$$

and

$$\min \phi_{k0}$$

$$\text{subject to:} \begin{cases} \sum_{j=1}^{n} \lambda_j c_{kj} = \phi_{k0} \\ \sum_{j=1}^{n} \lambda_j c_{-kj} = c_{-k0}, -k = 1, \dots, k-1, k+1, \dots, s_2 \\ \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0}, i = 1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0}, r = 1, \dots, s_1 \\ \lambda_j = 0, j = 1, \dots, n \end{cases} \tag{3.5}$$

respectively, for $i = 1, \dots, m$, $r = 1, \dots, s_1$ and $k = 1, \dots s_2$.

From equations (3.3) – (3.5), x_{ij} denotes the input level used by DMU_j; y_{ij} denotes the quantity of output produced by DMU_j. m, s_1 and s_2 are the input observations, desirable output observations and undesirable output observations respectively. d_{i0} and ϕ_{k0} represent the inputs and undesirable outputs to be minimised whereas δ_{r0} represents the desirable outputs to be maximized. The ideal reference point $(d_{i0}^*, y_{r0}^*, c_{k0}^*)$ for each unit (x_{i0}, y_{r0}, c_{k0}) is obtained by solving the linear programming problems above.

The MEA efficiency of each variable for the production unit (x_{i0}, y_{r0}, c_{k0}) is derived as:

$$max(\beta_{i0} + \beta_{r0} + \beta_{k0})$$

$$\text{subject to} \begin{cases} \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{i0} - \beta_{i0}(x_{i0} - d_{i0}^*), i = 1, \dots, m \\ \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{r0} - \beta_{r0}(\delta_{i0}^* - y_{r0}), r = 1, \dots, s_1 \\ \sum_{j=1}^{n} \lambda_j c_{kj} = c_{k0} - \beta_{k0}(c_{k0} - \phi_{i0}^*), k = 1, \dots, s_2 \\ \lambda_j \geq 0, j = 1, \dots, n \end{cases} \tag{3.6}$$

$\beta_{r0}, \beta_{k0}, \beta_{i0}$ measures the proportion by which the desirable outputs are added while the undesirable outputs and inputs are contracted in the same proportion (Bi et al., 2014; Bogetoft & Hougaard, 1999; Kapelko & Lansink, 2017; Tziogkidis et al., 2020). β_{ij}, β_{rj} and β_{kj} always falls within the interval, [0,1] hence a DMU is said to have reached the frontier of the best practice firms if $\beta_{ij} = \beta_{rj} = \beta_{kj} = 0$ otherwise, the DMU is farther away from the frontier of the best practice firms (Asmild et al., 2003;Bi et al., 2014; Bogetoft & Hougaard, 1999; Kapelko & Lansink, 2017). Using the optimal solution, $(\lambda_j^*, \beta_{i0}^*, \beta_{r0}^*, \beta_{k0}^*)$, from equation (3.6), the benchmark selection (or the potential improvement point) for the target unit (x_{i0}, y_{r0}, c_{k0}) is determined as $(x_{i0}^*, y_{r0}^*, c_{k0}^*)$. The MEA efficiency values for the production unit and its specific variable efficiency scores are defined below:

For each input variable x_i, the MEA efficiency value is given as:

$$\theta_i = \frac{x_{i0} - \beta_{i0}^*(x_{i0} - d_{i0}^*)}{x_{i0}} \tag{3.7}$$

For each desirable output y_r, the MEA efficiency value is given as:

$$\theta_r = \frac{y_{r0}}{y_{r0}+\beta_{r0}^*(\delta_{r0}^*-y_{r0})} \tag{3.8}$$

Finally, for each undesirable output c_k, the MEA efficiency value is given as:

$$\theta_k = \frac{c_{k0}-\beta_{k0}^*(c_{k0}-\phi_{k0}^*)}{c_{k0}} \tag{3.9}$$

From the variable-specific MEA efficiency values above, the vector of relative variable-specific MEA efficiency for the production unit is given as:

$$\left(\frac{x_{i0}-\beta_{i0}^*(x_{i0}-d_{i0}^*)}{x_{i0}}, \frac{y_{r0}}{y_{r0}+\beta_{r0}^*(\delta_{r0}^*-y_{r0})}, \frac{c_{k0}-\beta_{k0}^*(c_{k0}-\phi_{k0}^*)}{c_{k0}}\right) \tag{3.10}$$

Using the variable-specific MEA efficiency values defined in equations (3.7) – (3.9) and based on the slack-based measure (SBM) model aggregation idea of Tone (2001), a comprehensive MEA efficiency is established consisting of all the input and output (desirable and undesirable) variables. From Zhu et al. (2019), the overall comprehensive MEA efficiency score is given as:

$$\theta_0 = \frac{1-\frac{1}{m}\sum_{i=1}^{m}\frac{\beta_{i0}^*(x_{i0}-d_{i0}^*)}{x_{i0}}}{1+\frac{1}{s_1+s_2}\left[\sum_{r=1}^{s_1}\frac{\beta_{r0}^*(\delta_{r0}^*-d_{r0})}{y_{r0}}+\sum_{k=1}^{s_2}\frac{\beta_{k0}^*(c_{k0}-\phi_{k0}^*)}{c_{k0}}\right]} \tag{3.11}$$

3.5 Nonparametric returns to scale assumption

Unlike other efficiency studies (Asmild et al., 2016; Barros et al., 2010; Lozano & Soltani, 2020) that assumed the return to scale (RTS) of an underlying technology of a study, this study tests to identify the appropriate return to scale of its technology following Ohene-Asare et al. (2017). The choice of the specific return to scale of an underlying technology is of great importance as changes in the choice of return to scale result in different conclusions (Ohene-Asare et al., 2017; Leopold Simar & Wilson, 2002). There exist various test approaches for testing the specific return to scale of an underlying technology (Banker, 1996; Barros et al., 2010; Leopold Simar & Wilson, 2002; Simar & Wilson, 2011). Fare and Grosskopf (1985) developed an approach for testing the local return to scale in an estimated frontier. However, the approach does not provide a formal statistical test of return to scale. Simar and Wilson (2002) further developed the global returns to scale of the bootstrap methodology, designed by Simar and Wilson (1998) considering the deterministic nature of non-parametric measures like DEA. This approach is used to test the return to scale of the underlying technology in the study. The approach is based on the hypotheses that:

$H_0 : \psi$ is globally CRS versus $H_1 : \psi$ is VRS (3.12)

Consistent with Simar and Wilson (2002) and Ohene-Asare et al. (2017), the test statistic of the mean of ratios ($\hat{S}_1$) and ratio of means ($\hat{S}_2$), is defined as

$$\hat{S}_1 = n^{-1} \sum_{j=1}^{n} \left[\frac{\hat{\varphi}_j^{CRS}(x,y)}{\hat{\varphi}_{\substack{3\\j}}^{VRS}(x,y)} \right] \tag{3.13}$$

$$\hat{S}_2 = \frac{\sum_{j=1}^{n} \hat{\varphi}_j^{CRS}(x,y)}{\sum_{j=1}^{n} \hat{\varphi}_j^{VRS}(x,y)} \tag{3.14}$$

where $\hat{\varphi}_j^{CRS}(x, y)$ and $\hat{\varphi}_j^{VRS}(x, y)$ represent the estimated technical efficiency scores assessed under the CRS and VRS assumptions respectively. When $\hat{\varphi}_j^{CRS}(x, y) = \hat{\varphi}_j^{VRS}(x, y)$ then $\hat{S}_i = 1, i = 1,2$ hence H_0 is true for all the DMUs ($j = 1,2, \ldots, n$). The test statistic developed by Simar and Wilson (2011), mean of ratios less unity ($\hat{S}_3$), is used to confirm the test results of the mean of ratios ($\hat{S}_1$) and ratio of means ($\hat{S}_2$).

$$\hat{S}_3 = n^{-1} \sum_{j=1}^{n} \left[\frac{\hat{\varphi}_j^{CRS}(x,y)}{\hat{\varphi}_j^{VRS}(x,y)} - 1 \right] \geq 0 \tag{3.15}$$

Since the distribution for $\widehat{S} = (\widehat{S}_1, \widehat{S}_2, \widehat{S}_3)$ and H_0 are not known, bootstrapping method is used to obtain the critical values and p-values of the tests (Ohene-Asare et al., 2017).

3.6 Second stage regression analysis

Over time the efficiency assessment of decision-making units (DMU) has become incomplete without regressing environmental variables to the efficiencies, second-stage analysis. Daraio and Simar (2007) explained that the non-parametric efficiency model, DEA, is sensitive to outliers and sampling variations hence it is not appropriate to solely depend on its efficiency scores to make statistical inferences. In addition, environmental variations around firms cannot be ignored due to the direct impact these variations have on firm performance (Dyson et al., 2001). Hence, the assessment of the robustness of non-parametric efficiency scores cannot be left unattended during efficiency assessment. As a result, several non-parametric efficiency studies consider the two-stage approach; assess efficiency in the first stage and then regress the estimated efficiencies on some environmental variables in the second stage (Simar & Wilson, 2007).

Different second-stage regression models have been used in various industries (Asmild & Matthews, 2012; Hanif Akhtar, 2013; Molinos-Senante et al., 2016; Zhang & Lin, 2018) including insurance (Alhassan & Biekpe, 2016; Ansah-Adu et al., 2012; Barros et al., 2010; Barros & Dieke, 2008; Kader et al., 2014). However, two of these regression models; Tobit and ordinary least square (OLS) have been strongly criticised due to their failure to consider the presence of serial correlation in non-parametric, DEA, efficiencies estimates and the absence of proper data generating process (McDonald, 2009; Ramalho et al., 2010; Simar & Wilson, 2007). Simar and Wilson's truncated-bootstrapped regression model on the other hand is believed to have specified a coherent data generating process and hence provides consistent and valid regression results.

Many insurance efficiency studies have adopted this regression model so as to obtain consistent and unbiased second-stage estimates irrespective of the correlation between the first stage efficiency estimates and the exogenous variables (Alhassan & Biekpe, 2015; Barros et al., 2010; Barros & Wanke, 2014; Luhnen, 2009). However, this study uses the pooled OLS, fixed effect, random effect, Beck and Katz (1995) for panel-corrected standard errors, Driscoll and Kraay (1998) spatial correlation consistent (SCC) and the two-step system GMM regression to crosscheck the robustness of the MEA efficiency scores.

First, the pooled OLS is a widely used regression estimation technique in panel data. It is simple to perform as it does not require the use of any special technique. It is usually used as the baseline model for most pooled analysis (Stimson, 1985). The model assumes all entities (insurers) to operate in the same way over a period of time (Wooldridge, 2002). However, its demerit lies in its inability to consider the differences within entities and time variations (time effects) (Stimson, 1985). Stimson (1985) posits OLS to be only acceptable for a given research question, nonetheless without using other regression models there is no satisfactory method to tell its appropriateness.

Second, the fixed effect model explores the link between the predictor and the outcome variables within an entity. It assumes correlation between the entity specific effect and predictors (Nickel, 1981). The model assumes the time-invariant characteristics to be unique to the entity, and does not expect any correlation to exist with other individual characteristics, dummy variables (Bell & Jones, 2015). Xu (2017) and Plumber, Troeger and Manow (2005) believe its exogenous variables to contain unit-specific dummy variables which allow its intercepts to vary by unit. The model in addition controls for all time-variant differences among entities, as a result, omitted time-invariant characteristics cannot cause its estimated coefficient to be bias. Unlike the pooled OLS estimation technique, the fixed effect estimator addresses the omitted variable bias by controlling for fixed effects, but has the tendency of compounding the problem of measurement error (Hauk & Wacziarg, 2009).

Third, unlike the fixed effect model which assumes correlation for the predictor and outcome variables, the random effect model assumes no correlation between unobserved entity-specific, time-invariant and regressors (Torres-Reyna, 2007). That is, it assumes variation across entities to be random, correlated with the predictor or independent variables in the model. Bhargava et al, (2001) suggests that although entity-specific, time-invariant and explanatory variables are uncorrelated, the impact of such unobserved variables must be specified in the regression model. Random effect therefore, uses all available data, produces unbiased parameter estimate and smaller standard error, however its unobserved entity-specific, time-invariant variable produce omitted variable bias. An advantage of this technique over the fixed effect is the presence of time invariant variables. (Gunasekara et al. 2014; Firebaugh, Warner & Massogila, 2013).

Fourth, the two-step system GMM is a variant of the system-GMM method. It has been proven to be more efficient than its counterpart; one-step system GMM (Agbloyor et al., 2016). It is usually used to estimate the dynamic frontier with time-invariant technical efficiency (Bhattacharyya, 2012). The method uses a set of moment conditions relating to the first differenced regression equation, and another set of moment conditions for the regression equation (Blundell and Bond, 1998). Unlike the difference GMM which deducts the initial observations from the contemporaneous ones, thus enlarging the gaps in the case of panel data which is unbalanced (Arellano & Bond, 1991), the system-GMM method subtracts only the averages of the observations available from the current and future ones, and hence ends up reducing the gaps in the dataset. According to Arellano and Blover (1995) and Blundell and Bond (1998), the system-GMM method has an advantage of improving the difference-GMM by way of equation supplementation in the first difference with the level equations.

These econometric models are used in line with Wooldridge (2009), to deal with data and model specifications such as multicollinearity, heteroskedasticity and serial correlation.

3.6.1 Econometric tests

Preceding the selection of the appropriate econometric regression model for the study, the correlation matrix in addition to the variance inflation factors (VIFs) are used to test for multicollinearity in the study data. The Chow test in addition to other econometric tests are undertaken to ensure the selection of a robust model.

First, to test for poolability of the study's panel data, the Chow test is conducted with the null hypothesis,

H_0: dataset is poolable versus H_1: dataset is not poolable

The test statistic of the Chow test is given as:

$$F_{1-way} = \frac{(ESS_R - ESS_U)/(N-1)}{(ESS_U)/((T-1)N-K)} \tag{3.16}$$

where ESS_R denotes the residual sum of squares under the H_0; ESS_U denotes the residual sum of squares of the H_1. H_0 is rejected if the test statistic is significant (p-value < 0.05) and conclude that no panel models need to be specified, as all individuals are sufficiently homogenous (Brooks, 2008).

Second, the presence of autocorrelation/serial correlation is tested with the Breusch-Godfrey (1981) and Wooldridge (2002) since time dependency in panel data brings about serial correlation of the errors and substantial autocorrelation in the unobserved individual specific effects u_i makes the heteroskedasticity-robust standard errors inconsistent. The test statistic of the Breusch-Godfrey (1981) test is given as:

$$L_{\delta^2_{u=0}}(\rho = 0) = \frac{NT^2}{(T-1)}\beta^2 X^2(1)$$

$$LM_{fixed\ effects}(\rho = 0) = \frac{NT^2}{(T-1)}\frac{\hat{e}'\hat{e}_{-1}}{\hat{e}'\hat{e}} \sim X^2(1) \tag{3.17}$$

$\hat{e} = \tilde{y} - \tilde{y}\hat{\beta}$ = residual of mean deviation regression

The Wooldridge (2002) test statistic which tests the null hypothesis, H_0, that there exist no unobserved effects in the residuals is given as:

$$W = \frac{\sum_{i=1}^{n}\sum_{t=1}^{T-1}\sum_{s=t+1}^{T}\hat{\varepsilon}_{it'}\hat{\varepsilon}_{is}}{\left[\sum_{i=1}^{n}(\sum_{t=1}^{T-1}\sum_{s=t+1}^{T}\hat{\varepsilon}_{it'}\hat{\varepsilon}_{is})^2\right]^{\frac{1}{2}}} \tag{3.18}$$

where $\hat{\varepsilon}_{it}$ and $\hat{\varepsilon}_{is}$ are the pooled OLS residuals.

Third, to determine whether a fixed effect model (FE) or a random effect model (RE) is appropriate for this study, a Durbin-Wu-Hausman test (Durbin, 1954; Hausman, 1978; Wu, 1973) is undertaken. The Hausman test statistic is given by:

$$H = (\hat{\beta}_{RE} - \hat{\beta}_{FE})'\left[Var(\hat{\beta}_{RE}) - Var(\hat{\beta}_{FE})\right]^{-1}(\hat{\beta}_{RE} - \hat{\beta}_{RE}) \sim X^2(k) \tag{3.19}$$

Its null hypothesis says that the unobserved individual-specific effects μ_i is correlated with all the exogenous variables, x_{ij}, that is, the RE model is appropriate. Hence, the FE model is chosen if the test statistic is significant ($p < 0.05$), H_0 is rejected and the RE model is used if otherwise, the test statistic is insignificant.

Next, the Breusch-Pagan (1979, 1980) Lagrange Multiplier (LM) test of independence and the Pesaran (2006) Cross-sectional Dependence (CD) test are used to test for cross-sectional dependence. The LM test statistic for $T \rightarrow \infty$ is given by

$$LM = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} T_{ij} \hat{\rho}_{ij}, \tag{3.20}$$

Where $\hat{\rho}_{ij}$ is the simple estimate of the pairwise correlation of the residual. The statistic is distributed as X^2 with $N(N-1)/2$ degrees of freedom. This test is not applicable when $n \rightarrow \infty$ hence a scaled version of the Pesaran (2006) CD test is used. Its test statistic is given as

$$CD = \sqrt{\frac{2}{n(n-1)}} \left(\sum_{i=1}^{n-1} \sum_{j=i+1}^{n} T_{ij} \hat{\rho}_{ij} \right) \tag{3.21}$$

The null hypothesis of the Pesaran (2006) CD test which is asymptotically distributed suggests no cross-sectional dependence, $CD \overset{d}{\rightarrow} N(0,1)$ for $n \rightarrow \infty$ with T being sufficiently large.

The Newey-West (1987) kernel-based robust heteroskedastic autocorrelation consistent (HAC) variance estimator is also used in this study. This estimator is used to restrict the cross-sectional and cross-serial correlation to zero to overcome the serial correlation and heteroskedasticity present in the error terms. In addition to the HAC estimator, the Driscoll and Kraay (1998) SCC estimator is used to produce robust standard errors.

Finally, the unconditional robust covariance matrix estimators of Beck and Katz (1995) for panel models, usually known as Panel Corrected Standard Errors (PSCE) is employed in the study. The PCSE estimate is robust against unit cross-correlation heteroscedasticity and contemporaneous correlation across the i groups $E(\varepsilon_{it}, \varepsilon_{jt}|X)=\sigma_{ij}$, common in panel data.

3.6.2 Panel data econometric models

The first stage MEA efficiency score is considered as the dependent variable explained by the insurance specific factors, competition, leverage, size, solvency, profitability, line of business and underwriting risk (Table 3.2). The insurance specific factors were employed for this study are examined with an array of econometric techniques so as to establish the strength of the results. The baseline panel model is formulated as:

$$Eff_{i,t} = \beta_1 comp_{i,t} + \beta_2 lev_{i,t} + \beta_3 size_{i,t} + \beta_4 solv_{i,t} + \beta_5 roa_{i,t} + \beta_6 type_i + \beta_7 Underisk_{i,t} + \delta Eff_{i,t-1} + \sum_{t=2008}^{2019} Year_t + \sum_{i=1}^{30} Insurer_i + \varepsilon_{i,t} \quad \varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2) \qquad (3.22)$$

where; $Eff_{i,t}$ = MEA efficiency score of insurer i at time t.

β_i= parameters to be estimated to assess the extent to which each explanatory variable influences the dependent variable.

$comp_{i,t}$ = competition among insurers proxied as Boone indicator for insurer i.

$Eff_{i,t-1}$ = the previous year's MEA efficiency score.

$lev_{i,t}$ = leverage ratio of insurer i at time t.

$type_i$ = dummy variable with a value of 1 if the insurer deals with life business and 0 otherwise.

$size_{i,t}$ = size of insurer i at time t.

$solv_{i,t}$ = solvency of insurer i at time t proxied with the z-score.

$roa_{i,t}$ = profitability of insurer i at time t proxied as the return on asset.

$Underisk_{i,t}$ = underwriting risk of insurer i at time t.

$\sum_{t=2008}^{2019} Year_t$, $\sum_{i=1}^{30} Insurer_i$, $\sum_{i=1}^{30} Insurer_i + \varepsilon_{i,t}$ = time dependent effect, unobserved individual specific effect and the error term respectively. These are based on the assumption that the residuals are normally distributed with a zero mean and a constant standard variation, $\varepsilon_{i,t} \sim N(0, \sigma_\varepsilon^2)$. The subscripts; i and t denote the insurers being considered and the time period of the study respectively.

The regressors/explanatory variables of the baseline regression model are further discussed in Section 3.9.3 of this same chapter.

The baseline regression models are formulated to suit the various regression models as follows:

The Fixed effect model:

$$Eff_{i,t} = \beta_1 comp_{i,t} + \beta_2 lev_{i,t} + \beta_3 size_{i,t} + \beta_4 solv_{i,t} + \beta_5 roa_{i,t} + \beta_6 Underisk_{i,t} + \delta Eff_{i,t-1} + \sum_{t=2008}^{2019} Year_t + \varepsilon_{i,t} \quad (3.23)$$

The Random effect model:

$$Eff_{i,t} = \alpha_1 comp_{i,t} + \alpha_2 lev_{i,t} + \alpha_3 size_{i,t} + \alpha_4 solv_{i,t} + \alpha_5 roa_{i,t} + \alpha_6 type_i + \alpha_7 Underisk_{i,t} + \sigma Eff_{i,t-1} + \sum_{i=1}^{30} Insurer_i + \varepsilon_{i,t} \quad (3.24)$$

Two-step system generalised method of moments (GMM)

$$Eff_{i,t} = \omega Eff_{i,t-1} + \varphi_1 comp_{i,t} + \varphi_2 lev_{i,t} + \varphi_3 size_{i,t} + \varphi_4 solv_{i,t} + \varphi_5 roa_{i,t} + \varphi_6 type_i + \varphi_7 Underisk_{i,t} + \sum_{i=1}^{30} Insurer_i + \varepsilon_{i,t} \quad (3.25)$$

where $i = 1,2, \ldots, 30$; $t = 1,2, \ldots, 12$.

3.7 Data and variables selection

The output of insurers includes services (Cummins & Weiss, 1993). However, the actual products produced by financial service providers received long-standing disagreements until Berger and Humphrey (1992) proposed three methods for selecting the outputs and inputs of the services provided by insurers. The proposed methods are the asset approach, user-cost approach and the value-added approach.

First of all, the asset approach, also known as the intermediation approach, is an approach which views financial firms as financial intermediaries between owners of liabilities and the fund receivers of financial firms (Berger & Humphrey, 1992). Acting as financial intermediaries, they borrow funds from liability holders, transform the funds into assets and pay interest for the value of money lost (Cummins & Weiss, 2000). While life insurers invest the premiums received awaiting the occurrence of an insured loss, property-liability insurers offer advice and replace damaged insured properties. As a result, this approach cannot be used in the insurance sector since property-liability insurers offer services beyond financial intermediation (Cummins & Weiss, 2013).

Second, the user-cost approach is an output measure which uses a financial product's net contribution on revenue to determine whether the product is an input or output (Berger & Humphrey, 1992; Hancock, 1985). This output measure compares the financial return on an asset and the opportunity cost of funds with the opportunity cost. Cummins and Weiss (2013) postulated that a financial product is considered as an output if its financial return on an asset exceeds the opportunity cost of funds or if the financial cost of a liability is less than the opportunity cost. However, Berger and Humphrey (1992) identified some setbacks in the application of this approach to the banking sector. They explain that the user-cost approach is sensitive to the turning of outputs into inputs and vice versa, in addition, the approach rides on the basis of excluded operating cost. Cummins and Weiss (2013) also explained that the user-cost approach is problematic for the insurance sector since insurance policies consist of a lot of services which are not all priced explicitly.

The last approach for measuring output is the value-added approach. It is the best and most appropriate approach for assessing insurance sectors (Chen et al., 2009; Cummins & Weiss, 2013). Rather than distinguishing outputs from inputs in a mutually exclusive way like the user-cost approach and the asset approach, the value-added approach considers all liability and asset categories to possess some output characteristics (Berger & Humphrey, 1992). That is, assets and liabilities that add significant value to the financial institution are considered as output whereas those that do not add much value like expenses considered as inputs (Berger et al., 1997; Kasman & Turgutlu, 2009). This approach reflects the three principal services provided by insurers; risk-pooling and risk-bearing, intermediations, and real financial services related to insured losses (Chen et al., 2009; Eling & Luhnen, 2010). In line with previous insurance efficiency literature (Alhassan & Biekpe, 2015; Cummins et al., 1999; Cummins & Rubio-misas, 2006; Danquah et al., 2018; Eling & Luhnen, 2010), the value-added approach is used to measure the outputs of this study.

3.7.1 Insurance provided services

In comparison with other financial services, insurers provide intangible outputs hence, it is imperative to find appropriate proxies for their output services (Cummins et al., 2010; Cummins & Rubio-misas, 2006; Cummins & Weiss, 2000). This section discusses the three principal services insurers provide.

3.8.1.1 Risk-pooling and risk-bearing

Insurers provide a system for consumers and businesses exposed to insurable risk as they reduce their risk as insurers pool the risk (Cummins et al., 1999; Cummins & Weiss, 2000). They bear the risk of individuals and organizations in exchange for premiums which are invested to pay claims in the future. Some risks exposed to life insurers include the risk of death, risk of longevity and risk of loss from accident or illness (Cummins et al., 1999) whereas those exposed to non-life insurers include the risk of theft, liability risk and risk of motor accident. Cummins and Weiss (2000) believe that actuarial, underwriting and related expenses in pooling risk are major components of the value-added in the risk-pooling and risk-bearing function.

3.8.1.2 Real financial services relating to insured losses

Both life and non-life insurers provide a variety of real services to policyholders. While life insurers provide personal financial planning and administer group life policies with annuities (Cummins et al., 1999), non-life insurers organize risk surveys, design coverage programs and make recommendations on deductibles and policy limits (Cummins & Weiss, 2000).

3.8.1.3 Financial intermediation

Insurers being aware of the contribution added to their revenue from the accumulation of assets, issue debt contracts to policyholders and invest the premiums received in advance to traded securities and assets (Cummins et al., 1999). Insurers either use the interest they get from the investment to pay off the losses suffered by their policyholders or offer premium discounts to these policyholders. That is to say, life insurers that sell asset accumulation products like annuities, make direct credit to policyholders' account to reflect investment income for the policyholders whereas property - liability insurers offer premium discounts to their policyholders (Cummins & Rubio-misas, 2006; Cummins & Weiss, 2000; Kaffash et al., 2020). Under this type of service provided by insurers, the net interest margin between the rate of return earned on the invested assets and the rate credited to policyholders depicts the source of value-added (Cummins et al., 1999; Cummins & Weiss, 2000) to the insurer.

3.8 Modelling inputs and outputs

For any efficiency analysis, the definition of inputs and outputs plays a crucial role as it determines whether a particular efficiency analysis would be meaningless or useful (Cummins & Weiss, 2013). This study follows the convention in insurance efficiency literature to define its inputs and outputs. The study's outputs and inputs are discussed in the sections below.

3.8.1 Outputs

According to Diacon et al. (2002), outputs are goods and services sold to customers to generate revenue. Outputs chosen for this study are based on the value-added approach since it reflects the basic services offered by insurers. The outputs chosen for this study are discussed below.

3.8.1.1 Investment income

Consistent with the studies of Al-Amri (2015) and Alhassan and Biekpe (2016), this study refrains from using invested assets as the output proxy for intermediation. Cummins and Weiss (2013) are of the view that because insurers collect premiums in advance, investment income must be included and appropriately measured when measuring insurance output in insurance efficiency assessment. Hence, investment income is used as an output variable to proxy for intermediation in this study following Ohene-Asare et al. (2019), Berger et al. (1997 and Cummins and Weiss

(2000). Resulting from the returns insurers receive from investment income, investment income is used as a desirable output (good output) in this study; insurers desire to increase the amount of investment income received (Cooper et al., 2004; Seiford & Zhu, 2002). The value for investment income is obtained from the statement of comprehensive income of the annual report of the sample insurers.

3.8.1.2 Net premium

While some researchers like Diacon et al. (2002) see net premium as one of the available best proxies for the risk-pooling and risk-bearing function, others like Alhassan and Ohene-Asare (2016), Cummins and Rubio-misas (2006), Cummins and Weiss (2013), Yuengert (1993) have strongly criticized the use of net premium as a proxy for the risk-pooling and risk-bearing function of insurance. These critics arose from the assertion that premium is a revenue, a product of price and output, and not just an output, hence it does not qualify to be an output proxy for insurers. Nevertheless, the net premium is one of the most used outputs in insurance efficiency (Diacon et al., 2002; Kaffash et al., 2020). Consistent with previous insurance efficiency literature, Ansah-Adu et al. (2012), Bikker and van Leuvensteijn (2008), Diacon et al. (2002), Ohene-Asare et al. (2019) and Rai (1996), net premium, is used as an output proxy for the risk-pooling and risk-bearing function of the insurers' principle. Its value is obtained from the statement of comprehensive income of the sampled insurers. It is used as a desired output (good output) since insurers have the opportunity to receive premiums in advance and are able to make returns from it usually before the occurrence of a covered loss (Cooper et al., 2004; Seiford & Zhu, 2002).

3.8.1.3 Claims

The selection of claims as an input or output has been argued in different insurance efficiency studies however, there is no obvious trend in literature specifying the ideal use of claims for appropriate insurance efficiency assessment (Gaganis et al., 2013). Studies like Gaganis et al. (2013), Rai (1996), Wu et al. (2007), Yang (2006), Yao et al. (2007) captured claims as an input, with the analogy that, claims forms part of insurer's expenses, hence must be minimized. But this study follows the assertion of Diacon et al. (2002) and Reyna and Fuentes (2018); management is not interested in increasing claims payment even though it qualifies to be an output variable. As a result, claims are considered as an undesirable output (bad output) in this study. Claims are proxied as net incurred claims/benefits incurred in this study. See the work of Gaganis et al. (2013). The value for net incurred claims/benefits incurred is obtained from the statement of comprehensive income of the sampled insurers.

3.8.2 Inputs

Inputs are used to produce the outputs. In insurance efficiency, labour and capital are agreed to be used as inputs and have been used in most studies (Diacon et al., 2002; Kaffash et al., 2020). These variables; labour and equity capital are used as inputs in this study in addition to fixed assets.

3.8.2.1 Fixed asset

In line with Ansah-Adu et al. (2012), Gardner and Grace (1993) and Owusu-Ansah et al. (2010), fixed asset, usually captured as physical capital, is used as one of the insurance inputs. Owusu-Ansah et al. (2010) postulate that fixed asset is in the form of physical assets; they include furniture, fittings, office space, plant and equipment (Gardner & Grace, 1993). Because of the constraints in data, fixed assets are measured by the expenses made on property, plant and equipment instead of the value fixed for capital assets. This value is obtained from the statement of financial position of the sampled insurers.

3.8.2.2 Labour

Labour is divided into two main categories; home-office labour and agent labour (Lim et al., 2020; Owusu-Ansah et al., 2010). The home-office labour represents the number of full-time office employees while agent labour represents the number of agents (Wang et al. 2007). In line with the studies of Barros et al. (2010), Biener et al. (2016), Cummins and Rubio-misas (2006), Danquah et al. (2018) and Kao and Hwang (2008), labour is used as an input variable in this study. Due to data unavailability, most insurance efficiency studies (Alhassan et al., 2015; Lim et al., 2020; Ohene-Asare et al., 2019) have used operating expenses as a proxy for labour, hence this study use this proxy for labour. Its value is obtained from the statement of comprehensive income of the sampled insurers.

3.8.2.3 Equity capital

Equity capital is used in most insurance efficiency studies. Among the 132 studies surveyed by Kaffash et al. (2020), less than 40% used equity capital as a measure of insurers' input. They include Alhassan et al. (2015), Alhassan and Biekpe (2016), Barros et al. (2010), Biener et al. (2016), Danquah et al. (2018), Diacon et al. (2002) and Ohene-Asare et al. (2019). In accordance with these studies, this study uses equity capital as an insurer's input and proxied as total equity. Details of the total equity of the sampled insurers were retrieved from the statement of financial position of their audited annual report.

3.8.3 Second stage variables

Taking motivation from Alhassan and Biekpe (2016) and Ansah-Adu et al. (2012), this study uses competition, profitability, leverage, firm size, competition, underwriting risk, solvency and type of insurer as exogenous covariates to identify the determinants of the MEA insurance efficiency of Ghanaian insurers.

3.8.3.1 Competition

The relationship between efficiency and competition has been studied by numerous researchers over the years (Alhassan & Biekpe, 2016; Alhassan & Ohene-Asare, 2016; Barros et al., 2010; Ho & Hsu, 2021; Huang et al., 2018). Two main approaches are usually used to measure competition; the structural approach or the traditional international organisation and the non-structural approach or the new empirical international organization approach (Boone, 2008; Färe et al., 2015; Huang et al., 2018). The structural approach is based on the structure-conduct-performance (SCP) paradigm and uses market concentration indices like Herfindahl Hirschman Index (HHI), concentration ratios and market shares, as proxy for market power (Alhassan et al., 2015; Huang et al., 2018). The non-structural approach uses the theory of firm models under equilibrium conditions to measure competition, it's measures include the Lerner index, H-statistic and Boone.

Table 3.1. Description of first stage variables

Value-added approach		
Variable	**Description**	**Empirical application**
Inputs		
Fixed Asset	Property, plant and equipment	Ansah-Adu et al. (2012), Gardner & Grace (1993), Owusu-Ansah et al. (2010), Asmild and Matthew (2012), Nourani et al. (2018)
Labour	Operating expenses	Barros et al. (2010), Biener et al. (2016), Cummins & Rubio-misas (2006), Danquah et al. (2018), Kao and Hwang (2008), Alhassan and Biekpe (2016)
Equity Capital	Total equity	Alhassan et al. (2015), Alhassan & Biekpe (2016), Barros et al. (2010), Biener et al. (2016), Danquah et al. (2018), Diacon et al. (2002) and Ohene-Asare et al. (2019), Cummins et al. (2004)
Outputs		
Desired Output		
Net premium	Net premium written	Alhassan et al. (2015), Ansah-Adu et al. (2012), Ohene-Asare et al. (2019) Diacon et al. (2002), Gaganis et al. (2013)
Investment income	Income generated from investment.	Ansah-Adu et al (2012), Bikker and van Leuvensteijn (2008), Diacon et al. (2002), Ohene-Asare et al. (2019), Rai (1996)
Undesired Output		
Claims	Net incurred claims	Reyna & Fuentes (2018)

Indicator (BI) (Boone, 2008; Färe et al., 2015; Lerner, 1934). Even though the measures of the structural approach are simple to compute, they are non-monotone with competition, hence this study uses the Boone indicator, a non-structural approach, as a proxy measure for competition (Boone, 2008; Cummins et al., 2017). The Boone indicator, as postulated by Boone (2001, 2008) is based on the efficient structure hypothesis of Demsetz (1973). It is an indirect competition measure which examines competition with the idea that the competition rewards efficiency but punishes inefficiency (Cummins et al., 2017; Schaeck & Cih, 2014; van Leuvensteijn et al., 2011). Hence, in very competitive markets, firms with lower marginal cost (very efficient firms) get higher market shares, that is, the relationship between efficiency differences and performance differences is stronger in a competitive market (Bikker & van Leuvensteijn, 2008; Schaeck & Cih, 2014; van Leuvensteijn et al., 2011). Consistent with Alhassan and Ohene-Asare (2016)(van Leuvensteijn et al., 2011) and Cummins et al. (2017) Boone indicator is estimated of competition is given as:

$$In(\pi_i) = \alpha + \beta In(mc_i) + \varepsilon_i \tag{3.25}$$

From equation (3.22), π_i is the profit of insurer i as a proportion of its total assets; mc_i measures the marginal costs of each insurer i; β denotes the Boone indicator; α is a constant and ε_i is the error term. Firms with $\beta < 0$ are competitive whereas firms with $\beta > 0$ are collusive and uncompetitive (Alhassan & Biekpe, 2016; Schaeck & Cih, 2014).

In line with Alhassan and Biekpe (2018), Boone (2008), Cummins et al. (2017), the profit of the insurer is the difference between total revenue and total cost, where total revenue is the sum of net premiums and investment income and total cost is the sum of operating expenses and claims incurred. Consistent with Alhassan and Biekpe (2018) and Cummins and Weiss (1993), the translog cost function is used to measure insurers' marginal cost. It is given as:

$$\ln\left(\frac{tc}{w_3}\right)_{i,t} = \alpha_1 lny_{j,t} + 0.5\alpha_2\left(lny_{i,t}\right)^2 + \alpha_3 \ln\left(\frac{w_1}{w_3}\right)_{i,t} + \alpha_4 \ln\left(\frac{w_2}{w_3}\right)_{i,t} + 0.5\left(\alpha_5 \ln\left(\frac{w_1}{w_3}\right)_{i,t}\right)^2 +$$

$$0.5\alpha_6\left(\ln\left(\frac{w_2}{w_3}\right)_{i,t}\right)^2 + \alpha_7\left(\ln\left(\frac{w_1}{w_3}\right)\ln\left(\frac{w_2}{w_3}\right)\right)_{i,t} + \alpha_8\left(lny_{j,t}\right)\ln\left(\frac{w_1}{w_3}\right)_{i,t} \quad (3.23) \; +$$

$$\alpha_9(lny_{i,t})\ln\left(\frac{w_1}{w_3}\right)_{i,t} + \alpha_{10}trend_t + \alpha_{11}0.5trend_t^{\ 2} + \alpha_{12}trend_t lny_{j,t} +$$

$$\alpha_9(lny_{i,t})\ln\left(\frac{w_1}{w_3}\right)_{i,t} + \alpha_9(lny_{j,t})\ln\left(\frac{w_1}{w_3}\right)_{i,t} + \varepsilon_i + \gamma_t + \mu_{i,t} \quad (3.26)$$

where i and t are insurer and time respectively**;** tc is the total cost; $y_{i,t}$ is the output produced by insurer i at time t; w_1, w_2, w_3 denote the input prices; $trend_t$ denotes the technological change; ε_i, γ_t *and* $\mu_{i,t}$ are firm specific effects, time specific effects and the unobserved error respectively. In line with previous insurance efficiency studies (Asmild & Matthews, 2012; Danquah et al., 2018; Ohene-Asare et al., 2017), this study assumes that inputs like fixed assets, labour and equity capital are used to produce the outputs of insurers. w_1, w_2, w_3 are the input prices for physical capital, labour and equity capital respectively. These prices are derived as physical capital expense divided by total assets (Gardner & Grace, 1993; Kader et al., 2014), operating expenses divided by total assets (Kader et al., 2014) and equity capital divided by total assets.

The translog cost function in equation (3.23) is normalized with w_3 to impose linear homogeneity conditions (Phan et al., 2016; Tan & Floros, 2018). The first derivative of the translog cost function, with respect to the product of output and average cost is estimated to find the marginal cost (Clark, Radić, & Sharipova, 2018; Kouki & Al-Nasser, 2017; Tan & Floros, 2018). The marginal cost is given by;

$$mc_{i,t} = \frac{\partial\left(\frac{tc}{w_3}\right)_{i,t}}{\partial y_{i,t}} = \frac{tc_{i,t}}{y_{i,t}}\left[\alpha_1 + \alpha_2 lny_{i,t} + \alpha_7 \ln\left(\frac{w_1}{w_3}\right)_{i,t} + \alpha_8 \ln\left(\frac{w_2}{w_3}\right)_{i,t} + \alpha_{11}trend_t\right] \quad (3.27)$$

3.8.3.2 Leverage

According to Alhassan et al. (2015), insurers obtain leverage from unearned premiums which results from unexpired policies and outstanding claim amount. While Ansah-Adu et al. (2012)

could not take a decision on the relationship between efficiency and leverage, Alhassan and Biekpe (2015) deduced an effect of leverage on technical, scale and allocative efficiency. In addition, Jensen (1986) identified a positive relationship between leverage and efficiency explaining the importance with reducing managerial slack and the pressure mounted on management from the binding role of leverage cause a positive effect of leverage on efficiency. In line with the studies of Kumbhakar et al., (2012), Kasman and Turgutlu (2009). The study expects a positive effect of leverage on efficiency and proxies leverage as a ratio of debt to total assets following Biener et al. (2016).

3.8.3.3 Size

Most two-stage efficiency studies choose firm size as a key environmental variable (Diacon et al., 2002) and observe a significant relationship between size and efficiency (Diacon et al., 2002; Ohene-Asare et al., 2019). However, the relationship between size and efficiency in the insurance sector is inconsistent. Ansah-Adu et al. (2012), Luhnen (2009) and Owusu-Ansah et al. (2010) identified a significant postive relationship while Cummins et al. (2010) found an inverse relationship between size and scale efficiency but a positive relationship for cost, revenue and profit efficiency. This study expects a significant relationship between insurer size and efficiency. Following Alhassan and Biekpe (2015), Ansah-Adu et al. (2012), Cummins et al. (2010), Diacon et al. (2002), this study uses the natural logarithm of total assets as a proxy for insurer size as the correlation coefficients between outputs, inputs and total assets from prior studies are usually extremely high.

3.8.3.4 Solvency

Solvency is the amount of capital insurers need during extreme economic conditions to meet financial obligations (Greene & Segal, 2004). The solvency of an insurer refers to the insurer's liquidity; the insurers' ability to quickly transform its assets into cash when the need arises. Whereas Brockett et al. (2004) found little influence of solvency on efficiency, Cummins and Rubio-Misas (2006) observed a significant relationship explaining that many small, inefficient and financially low-level insurers who were insolvent have been eliminated from the industry. Huang and Eling (2013) also observed that insurers with high safety on average receive greater efficiency scores. The z-score is used as a proxy for solvency in this study.

The z_{score_j} is an accounting measure which shows the number of standard deviations a return realization has to fall in order to deplete the firm's equity (Cummins et al., 2017). In line with Laeven and Levin (2009), Alhassan and Biekpe (2018), the z_{score_j} is used to measure solvency in this study. Following Beck et al. (2013) and Clark et al. (2018), the z_{score_j} is given as:

$$z_{score_j} = \frac{ROA_i + (E/A)_i}{|ROA_i - \overline{ROA_i}|} \tag{3.28}$$

From equation (3.25), ROA_i is the ratio of profit after tax to the total asset for insurer i. $(E/A)_i$ is the ratio of equity to assets for insurer i. $\overline{ROA_i}$ is the average return on assets for each insurer i for the entire study period. Since z_{score_j} is skewed the natural logarithm of the z-score is used following prior studies (Beck et al., 2013).

3.8.3.5 Profitability

According to Alhassan et al. (2015), efficiency drives the profitability of both life and non-life insurers. Greene and Segal (2004) find an inverse relationship between the inefficiency of US life insurers and profitability, measuring profitability as the ratio of return to equity (ROE). Return on asset (ROA) is an indicator of an insurers' profitability (NIC, 2012). It is "the efficiency with which management utilizes the assets of the company to generate returns for the various stakeholders" (NIC, 2012, p56). ROA is used as a proxy for insurer profitability in line with previous studies (Alhassan et al., 2015; Alhassan & Ohene-Asare, 2016; Greene & Segal, 2004). Based on Alhassan et al. (2015) and Alhassan and Ohene-Asare (2016) the return on assets of an insurer is given as

$$ROA_i = \frac{\text{profit after tax}_i}{\text{total assets}_i} \tag{3.29}$$

where $\text{profit after tax}_i$ denotes the profit after tax for insurer i and the total assets_i denotes the total assets for insurer i. Details on profit after tax and total assets of the sampled life and non-life insurers are retrieved from the statement of comprehensive income and financial position of their annual reports respectively.

3.8.3.6 Type of insurer

The relationship between efficiency and the type of insurance business, life or non-life, has received little attention in recent literature. This could be a result of the limited insurance efficiency studies that focused on the relationship between insurers' line of business and efficiency. Danquah et al. (2018) found a positive significant relationship between cost efficiency and insurers' line of business whereas Ansah-Adu et al. (2012) observed an insignificant relationship. Following Ansah-Adu et al. (2012), Ohene-Asare et al. (2019) and Danquah et al. (2018) dummy variables are used to proxy the two types of insurers; 0 for non-life insurers and 1 for life insurers.

3.8.3.7 Underwriting Risk

Underwriting risk shows the quality of insurer's underwriting policies (Alhassan & Biekpe, 2016). It reflects the level of risk involved in insurance businesses (Alhassan et al., 2015; Asare et al., 2017). Since high-risk policies demand high claims pay-outs (Alhassan et al., 2015), insurers who underwrite risky policies usually suffer high underwriting losses, making them less efficient (Alhassan & Biekpe, 2016). Nevertheless, risk could have a positive effect on efficiency when insurers sell less risky policies (Alhassan & Biekpe, 2016). Following the studies of Alhassan et al. (2015), Alhassan and Biekpe (2016) and Asare et al. (2017) underwriting risk is proxied as the ratio of incurred claims to net premiums. Details on incurred claims and net premiums are both retrieved from the statement of comprehensive income of the audited annual reports of the sampled insurers.

3.9 Instruments for data analysis

Data gathered for this study was analysed using basic descriptive measures and advanced statistical measures like t-tests and correlation test in addition to a non-parametric efficiency measure, MEA. R version 4.0.5 with the psych and Hmisc packages were used to generate the descriptive measures, t-test and correlation test of the study. The Benchmarking package of the same version of R is also used to obtain the efficiency scores.

3.10 Chapter summary

In this chapter, much clarity and explanations have been given to the scientific processes and assumptions adopted in the study. The positivist worldview and the quantitative research approach were used to evaluate the data gathered from the NIC, Ghana for this study. The modified MEA model of Asmild and Matthews (2012) and Zhu et al. (2019) is used for the non-oriented efficiency assessment under the CRS technology. The input and outputs used for this study are clearly explained and justified with at least five empirical applications. Finally, the second stage regression models and their variables are also explained in this chapter.

Table 3.2 Variable definition and expected signs

Variable	Definition	Empirical application	Expected Sign
Competition	Boone Indicator	Alhassan and Ohene-Asare (2016), Bikker and van Leuvensteijn (2008), Cummins et al. (2017), Schaeck and Cih, 2014, van Leuvensteijn et al. (2011)	+
Leverage	Debt/ total assets	Kumbhakar et al. (2012), Kasman & Turgutlu (2009), Alhassan et al. (2015), Biener et al. (2016) Ohene-Asare et al. (2019)	+
Solvency	z_{score_j}	Laeven and Levin (2009), Alhassan and Biekpe (2018), Beck et al. (2013), Clark et al. (2018), Cummins et al. 2017	±
Size	Ln (total assets)	Alhassan and Biekpe (2015), Ansah-Adu et al. (2012), Cummins et al. (2010), Diacon et al. (2002), Biener et al. (2016), Ohene-Asare et al. 2019)	±
Profitability	Return on Assets	Alhassan et al. (2015), Alhassan and Ohene-Asare (2016), Greene and Segal (2004)	+
Type of insurer	0 = non-life insurer 1 = life insurer	Ansah-Adu et al. (2012), Ohene-Asare et al. (2019) and Danquah et al. (2018)	±
Underwriting risk	Incurred claims/ net premium	Alhassan et al. (2015), Alhassan and Biekpe (2016) and Asare et al. (2017)	±

CHAPTER FOUR

DATA ANALYSIS AND DISCUSSION OF FINDINGS

4.1 Introduction

This chapter presents the results of the data analyses of hypothetical data and the study data. Discussions of the results are supported with previous empirical findings and theoretical arguments with the view of drawing inferences from the results. The chapter consists of two main sections - analysis of the hypothetical data and analysis of the study data. The section for the analysis of the study has three sub-sections one of which provides the basic statistics of the data; the descriptive statistics and correlation analysis of the pooled sampled and grouped (life and non-life insurers) data. The second sub-section presents the efficiency scores of the sampled insurers in line with the study's objectives and the last sub-section provides the second-stage regression results and their analysis.

4.2 Analysis of hypothetical data

In order to illustrate and compare the efficiency assessment of the MEA approach with the traditional DEA approach, 8 hypothetical insurers that use 2 inputs (X_1, X_2) to generate 1 output (Y) are considered. Table 4.1, Figure 4.1 and Figure 4.2 depicts the hypothetical DMUs.

Table 4.1: Illustrative data for hypothetical insurers.

DMU	X_1	X_2	Y
A	2	12	1
B	2	8	1
C	5	5	1
D	10	4	1
E	10	6	1
F	8	12	1
G	7	9	1
H	4	10	1

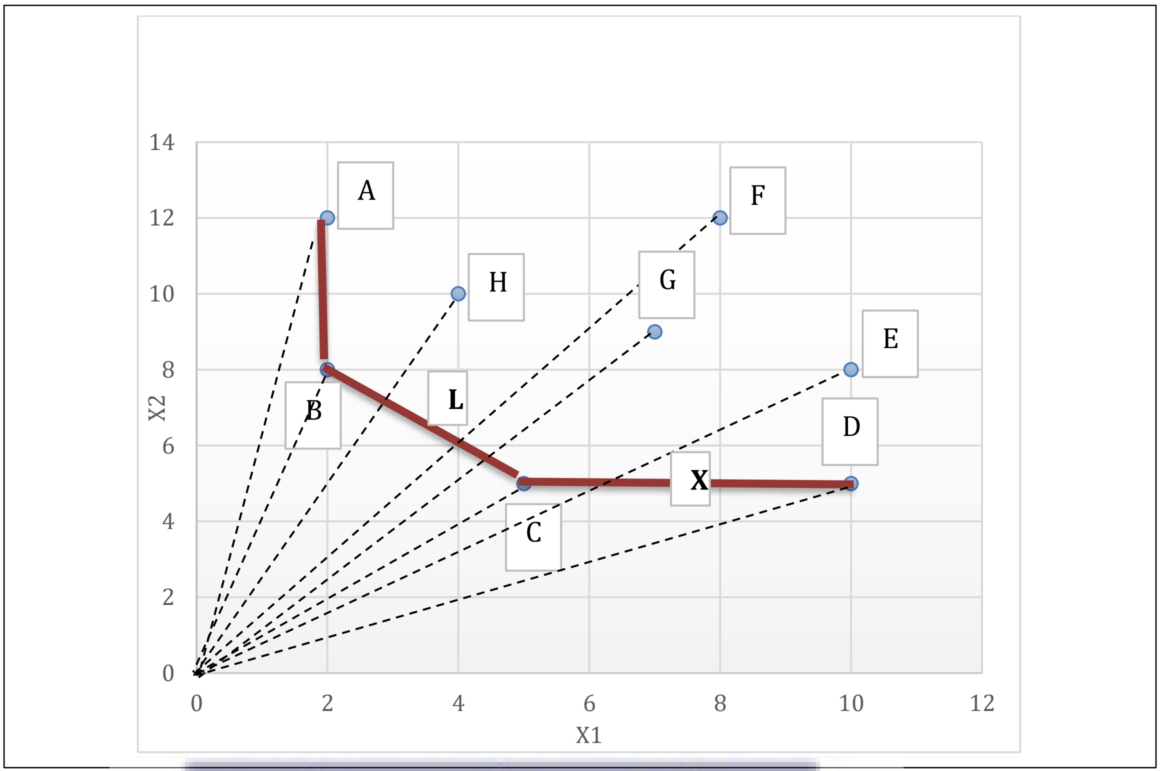
Figure 4.1 shows the DEA frontier defined by the linear combination of units A, B, C and D. Using Figure 4.1, the CCR (1978) DEA technical efficiency of a unit is defined as

$$TE(x, y) = \frac{\text{Distance from the origin to the production frontier}}{\text{Distance from the origin to the unit}}$$

Using unit F as an example the technical efficiency becomes:

$\frac{OL}{OF} = \frac{4}{8} = 0.50$ implying 50% technical efficiency.

Using a similar definition of technical efficiency, the TE score of all other DMUs are computed and presented in Table 4.2. The results show that units A, B, C and D are efficient. However, units E, F, G and H are not on the frontier (expressed in X in Figure 4.1) hence, inefficient. To identify the true benchmark for the inefficient firms, radial lines are drawn from the origin to meet the coordinates of the respective DMUs. The intersection between the radial line and frontier shows the benchmark point. From Figure 4.1, the true DEA benchmark for unit F is point L with coordinates (4, 6). That is, unit F becomes efficient when it reduces its inputs to 4 and 6 for X_1 and X_2 respectively. The distance between the coordinates of unit F and point L signifies the DEA input excess for unit F.



Source: Author's own construct, 2021

Figure 4.1: Graphical DEA solution for hypothetical data in input orientation.

Table 4.2: Manual computation of DEA input-oriented efficiency scores for all DMUs

DMUs	Efficiency	Decision
A	$\theta_A^* = \frac{2}{2} = 1$	Efficient
B	$\theta_B^* = \frac{2}{2} = 1$	Efficient
C	$\theta_C^* = \frac{5}{5} = 1$	Efficient
D	$\theta_D^* = \frac{10}{10} = 1$	Efficient
E	$\theta_E^* = \frac{6.5}{10} = 0.65$	Inefficient
F	$\theta_F^* = \frac{4}{8} = 0.5$	Inefficient
G	$\theta_G^* = \frac{4.5}{7} = 0.64$	Inefficient
H	$\theta_H^* = \frac{2.8}{4} = 0.7$	Inefficient

A DMU is efficient when its efficiency score is 1, otherwise, it is inefficient (Banker et al., 1984; Charnes et al., 1978).

The input-oriented variable returns to scale linear programming envelopment model that was formulated, using the information in Table 4.1, to assess the technical efficiency of unit F is given by

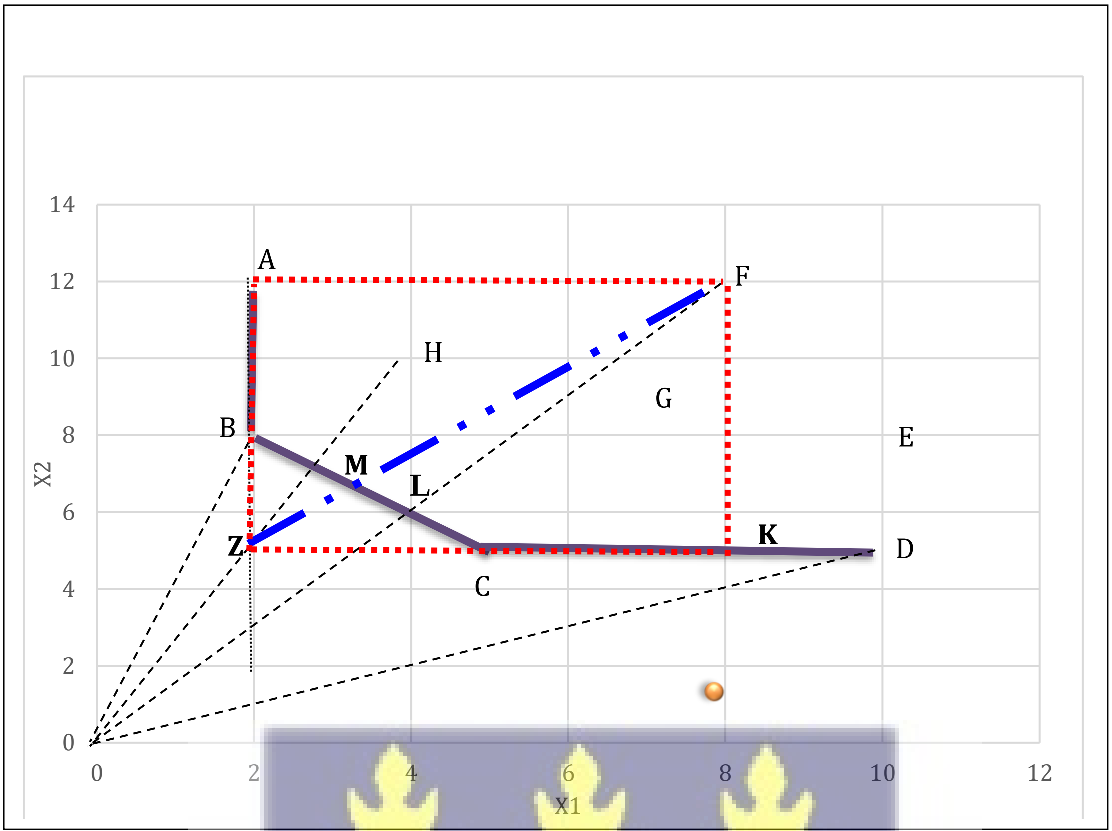
$$\theta_F^* = \min_{\lambda_j \theta} \theta$$

$$\text{s.t} \begin{cases} 2\lambda_1 + 2\lambda_2 + 5\lambda_3 + 10\lambda_4 + 10\lambda_5 + 8\lambda_6 \leq 8\theta \\ 12\lambda_1 + 8\lambda_2 + 5\lambda_3 + 4\lambda_4 + 6\lambda_5 + 12\lambda_6 \leq 12\theta \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 \geq 1 \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 = 1 \text{ (vrs)} \\ \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6 \geq 0 \end{cases}$$

The linear programming above can be solved with R

```
#In R with Benchmarking, DEA efficiency score is derived by the command “e$eff” after “e <- dea(x,y)”
e <- dea(x,y) #for running DEA LP
e$eff
[1] 1.0000000 1.0000000 1.0000000 1.0000000 0.6250000 0.5000000 0.6250000 0.7142857
e$lamb da
      L1   L2          L3         L4 L5 L6 L7 L8
[1,]  0  1.0000000    0.0000000    0  0  0  0  0
[2,]  0  1.0000000    0.0000000    0  0  0  0  0
[3,]  0  0.0000000    1.0000000    0  0  0  0  0
[4,]  0  0.0000000    1.0000000    0  0  0  0  0
[5,]  0  0.0000000    1.0000000    0  0  0  0  0
[6,]  0  0.3333333    0.6666667    0  0  0  0  0
[7,]  0  0.2083333    0.7916667    0  0  0  0  0
[8,]  0  0.7142857    0.2857143    0  0  0  0  0
```

In order to demonstrate the use of the MEA, using the same hypothetical data in Table 4.1, we draw in Figure 4.2, the input-specific MEA non-radial lines and the potential improvement points.



Source: Author's own construct, 2021

Figure 4.2: Graphical MEA input-specific solution for hypothetical data.

From Figure 4.2, unit F is obviously inefficient. To determine its inefficiency and hence demonstrate how to be efficient, instead of the original DEA radial contraction of the input X_1 and X_2, MEA first of all, identifies the improvement potential in each input (or output) dimension separately. In other words, a vertical line (signifying the reduction potential of input X_2) and a horizontal line (signifying the reduction potential of input X_1) are drawn from the F coordinates until they hit the boundary of the production possibility set. Combining the improvement potentials in all of the dimensions, as in this input-oriented graph, provides a (typically unobtainable) *ideal point Z* (the largest possible reduction point). The point where the DEA radial line intersects the frontier (point T) is the *DEA benchmark* in the direction of the origin. However, the point where the MEA non-radial line FZ intersects the frontier (expressed in K in Figure 4.2) (point M (3.3,6.6)) is the *MEA benchmark* in the direction of the ideal point. It can therefore be observed that, unlike DEA, MEA considers the shape of the part of the frontier, α, that dominates the point and selects a benchmark that is proportional to the improvement potentials. The MEA benchmark therefore has some desirable properties espoused by Bogetoft and Hougaard (1999) and Asmild et al. (2003) as explained earlier. For instance, whilst DEA selects weakly efficient benchmarks (A or D), MEA selects strongly efficient benchmarks (B or C).

Given the MEA formulae in equations (3.3) – (3.9), the MEA input-specific efficiency scores for unit F are computed using the linear programs below while assuming a variable returns to scale technology.

Stage 1: Find the **ideal reference point** for production unit (8,12) of DMU F

$$\min d_{1F}$$

$$\text{s.t} \begin{cases} 2\lambda_1 + 2\lambda_2 + 5\lambda_3 + 10\lambda_4 + 10\lambda_5 + 8\lambda_6 \leq d_{1F} \\ 12\lambda_1 + 8\lambda_2 + 5\lambda_3 + 4\lambda_4 + 6\lambda_5 + 12\lambda_6 \leq 12 \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 \geq 1 \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 = 1 \text{ (vrs)} \\ \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6 \geq 0 \end{cases}$$

$$\min d_{2F}$$

$$\text{s.t} \begin{cases} 2\lambda_1 + 2\lambda_2 + 5\lambda_3 + 10\lambda_4 + 10\lambda_5 + 8\lambda_6 \leq 8 \\ 12\lambda_1 + 8\lambda_2 + 5\lambda_3 + 4\lambda_4 + 6\lambda_5 + 12\lambda_6 \leq d_{2F} \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 \geq 1 \\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 = 1 \text{ (vrs)} \\ \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6 \geq 0 \end{cases}$$

From the input slacks values (`me$direct`) in the R output above, the ideal reference point for DMU F is computed as follows:

$$d_{1F}{}^* = (x_1 \text{ for } F - x_1 \text{ excess for } F)$$
$$d_{1F}{}^* = 8 - 6 = 2$$

$$d_{2F}{}^* = (x_2 \text{ for } F - x_2 \text{ excess for } F)$$
$$d_{2F}{}^* = 12 - 7 = 5$$

The ideal reference point for DMU F is $(d_{1F}{}^{*}, d_{2F}{}^{*}) = (2,5)$. The largest possible reductions for input X_1 and X_2 are 2 units and 5 units respectively.

The weights of the peers for unit F are given as

$\lambda_A = \lambda_E = \lambda_F = 0, \qquad \lambda_B = 0.5385,\ \lambda_C = 0.4615$

From the results above, the peers of inputs of unit F are units B and C. The associated weights are the proportion to which its inputs can mimic.

The coordinates of the ideal reference point for unit F are given as $(2,5)$ at point Z in Figure 4.2. This coordinate is infeasible as they lie outside the efficiency frontier. A second linear program is used to move the ideal reference point to the frontier to find the true benchmark (the potential improvement point). This clearly explains why DEA and MEA pick different benchmark points for each unit. The second linear programs maximise β, the proportion by which the inputs are contracted to make the ideal reference point feasible.

The linear programming above can be solved with R as:

```
###1ST STEP:  Identify ideal reference point###
mea.lines(c(6,6),x,y, ORIENTATION = "in")
require(Benchmarking)
hdata <- read.delim('clipboard')
x <- cbind(hdata1$x1[1:8],hdata1$x2[1:8])
y <- cbind(hdata1$y[1:8])
me <- mea(x,y)
[1] 1.0000 0.0000 0.0000 1.0000 0.7273 0.7692 0.6667 0.6667
me$direct
[,1]          [,2]
[1,]   0        4
[2,]   0        0
[3,]   0        0
[4,]   5        0
[5,]   8        3
[6,]   6        7
[7,]   5        4
[8,]   2        4


me$lambda #the weight of the peers, for each firm.
L1         L2              L3          L4  L5 L6  L7 L8
[1,] 0   1.0000000     0.0000000     0   0   0   0   0
[2,] 0   1.0000000     0.0000000     0   0   0   0   0
[3,] 0   0.0000000     1.0000000     0   0   0   0   0
[4,] 0   0.0000000     1.0000000     0   0   0   0   0
[5,] 0   0.2727273     0.7272727     0   0   0   0   0
[6,] 0   0.5384615     0.4615385     0   0   0   0   0
[7,] 0   0.4444444     0.5555556     0   0   0   0   0
[8,] 0   0.7777778     0.2222222     0   0   0   0   0
```

Stage 2: Finding the potential improvement point

$x_i^*(\text{DMU F}) = \beta\ (2,4.4)$

$max\ \ \beta$

$$\text{s.t}\begin{cases}2\lambda_1 + 2\lambda_2 + 5\lambda_3 + 10\lambda_4 + 10\lambda_5 + 4.5\lambda_6 \leq 4.5 - \beta(8-2)\\ 12\lambda_1 + 8\lambda_2 + 5\lambda_3 + 4\lambda_4 + 6\lambda_5 + 12\lambda_6 \leq 12 - \beta(12-5)\\ \lambda_1 + \lambda_2 + \lambda_3 + \lambda_4 + \lambda_5 + \lambda_6 \geq 1\\ \lambda_1, \lambda_2, \lambda_3, \lambda_4, \lambda_5, \lambda_6 \geq 0\end{cases}$$

The computation of the above LP was executed in R as:

```
me$eff  #In R with Benchmarking, beta is derived by the command "me$eff" after "me <- mea(x,y)"
[1] 1.0000000 0.0000000 0.0000000 1.0000000 0.7272727   0.7692308 0.6666667 0.6666667

peers(me)#In R with Benchmarking, target firms are derived by the command "peers(me)" after "me <- mea(x,y)"

       peer1       peer2
[1,]    2          NA
[2,]    2          NA
[3,]    3          NA
[4,]   3           NA
[5,]   2           3
[6,]   2           3
[7,]   2           3
[8,]   2           3
```

From the R output, the proportion by which the inputs X_1 and X_2 of unit F are to be contracted to make the ideal reference point Z, feasible is 0.7692, $\beta = 0.7692$.

Using β (0.7692), the potential improvement point, $S^{PI}(DMU\ F)$ is given as:

Input x_1^*

$x_1^* = x_1 - \beta(x_1 - d_{1F})$

$x_1^* = 8 - 0.7692(8 - 2)$

$x_1^* = 3.3848$

For input x_2^*

$x_2^* = x_2 - \beta(x_2 - d_{2F})$

$x_2^* = 12 - 0.7692(12 - 5)$

$x_2^* = 6.6156$

Alternatively, using λ the potential improvement points, $S^{PI}(DMU\ F)$ is given as:

Input x_1^*

$\boldsymbol{x_1^*} = L_2 \ * \ x_1$ of peer1 of DMU F $+ L_3 \ * x_1$ of peer2 of DMU F

$\boldsymbol{x_1^*} = 0.5384 * 2 + 0.4615 * 5 = 3.843$

Input x_2^*

$\boldsymbol{x_2^*} = L_2 \;\; * x_2$ of peer1 of DMU F $+ \; L_3 \;\; * x_2$ of peer2 of DMU F

$0.5384 * 8 + 0.4615 * 5 = 6.6147$

(3.8,6.6) is the potential improvement point for unit F. The coordinates of the point are interpretated as; unit F is efficient when it uses 3.8 units of input X_1 and 6.6 units of input X_2 to produce a unit of its output Y.

The relative input-specific (X_1, X_2) MEA efficiency scores for DMU F are computed as:

For input X_1:

$$\theta_{1F} = \frac{x_{1F} - \beta_{1F}^*(x_{1F} - d_{1F}^*)}{x_{1F}}$$

$$\theta_{1F} = \frac{8 - 0.7692(8-2)}{8}$$

$$\theta_{1F} = 0.4231$$

For input X_2:

$$\theta_{2F} = \frac{x_{2F} - \beta_{2F}^*(x_{2F} - d_{2F}^*)}{x_{2F}}$$

$$\theta_{2F} = \frac{12 - 0.7692(12-5)}{12}$$

$$\theta_{2F} = 0.5513$$

The vector of MEA input-specific efficiency score for unit F is

$$(\theta_{1F}, \theta_{2F}) = (0.4231, 0.5513).$$

The MEA input-specific efficiency score for unit F is 42.31% for input X_1 and 55.13% for input X_2. This means that generally, DMU F should be able to reduce its current input of X_1 by 57.69% (100% - 42.3%) and the current input of X_2 by 44.87% (100% - 55.13%) without reducing the current output level to become as efficient as its respective MEA efficiency reference sets (i.e MEA benchmark).

The relative input-specific MEA inefficiency scores are computed as:

For input X_1:

$$\sigma_{1F} = 1 - \theta_{1F}$$

$$\sigma_{1F} = 1 - \frac{x_{1F} - \beta_{1F}^*(x_{1F} - d_{1F}^*)}{x_{1F}}$$

$$\sigma_{1F} = 1 - \frac{8 - 0.7692(8-2)}{8}$$

$$\sigma_{1F} = 1 - 0.4231$$

$$\sigma_{1F} = 0.5769$$

For input X_2:

$$\sigma_{2F} = 1 - \theta_{2F}$$

$$\sigma_{2F} = 1 - \frac{x_{2F} - \beta_{2F}^*(x_{2F} - d_{2F}^*)}{x_{2F}}$$

$$\sigma_{2F} = 1 - \frac{12 - 0.7692(12-5)}{12}$$

$$\sigma_{2F} = 1 - 0.5513$$

$$\sigma_{2F} = 0.4487$$

The vector of MEA input-specific inefficiency score for unit F is $(\sigma_{1F}, \sigma_{2F}) = (0.5769, 0.4487)$.

The MEA input-specific inefficiency score for unit F is 57.69% for input X_1 and 44.87% for input X_2. This means that, for unit F to be efficient and produce at the target, (3.36, 6.62), unit F has to reduce the current quantity of input X_1 by 57.69% and the current quantity of input X_2 by 44.87%.

The overall MEA input-oriented efficiency score for unit F is given as

$$\theta_F = 1 - \frac{1}{m}\sum_{i=1}^{n} \beta_{iF}\left(\frac{x_{iF} - d_{iF}}{x_{iF}}\right)$$

$$\theta_F = 1 - \frac{1}{2}\left(\frac{\beta_{1F}^*(x_{1F} - d_{1F}^*)}{x_{1F}} + \frac{\beta_{2F}^*(x_{2F} - d_{2F}^*)}{x_{2F}}\right)$$

$$= 1 - \frac{1}{2}\left(\frac{0.7692(8-2)}{8} + \frac{0.7692(12-5)}{12}\right)$$

$$= 1 - \frac{1}{2}(0.5769 + 0.4487)$$

$$= 1 - \frac{1}{2}(1.0256)$$

$$= 1 - 0.5128$$

$$\theta_F = 0.4872$$

The overall MEA efficiency score of unit F is 48.72%. This signifies that unit F is utilising only 48.72% of all its inputs. In order to be efficient, unit F has to reduce its original inputs by 52% (100% - 48%).

After manually computing the DEA input-specific efficiency, ideal reference point, MEA comprehensive efficiency, MEA input-specific efficiency and inefficiency for unit F, R version 4.0.5 is used to compute these same values for all the hypothetical DMUs using the MEA and DEA models. All these values are presented in Table 4.3.

Table 4.3. MEA and DEA input-oriented efficiency scores of hypothetical insurers.

	A	B	C	D	E	F	G	H
X_1	2	2	5	10	10	**8**	7	4
X_2	12	8	5	5	8	**12**	9	10
y	1	1	1	1	1	**1**	1	1
X_1 excess	0	0	0	5	8	**6**	5	2
X_2 excess	4	0	0	0	3	**7**	4	4
β	1	0	0	1	0.72	**0.77**	0.67	0.67
Peer 1	B	B	C	C	C	**B**	C	C
Peer 2	NA	NA	NA	NA	C	**C**	C	C
λ_A	0	0	0	0	0	**0**	0	0
λ_B	1	1	0	0	0.27	**0.54**	0.44	0.78
λ_C	0	0	1	1	0.73	**0.46**	0.56	0.22
λ_D	0	0	0	0	0	**0**	0	0
λ_E	0	0	0	0	0	**0**	0	0
λ_F	0	0	0	0	0	**0**	0	0
λ_G	0	0	0	0	0	**0**	0	0
λ_H	0	0	0	0	0	**0**	0	0
d_{x1}^*	2	2	5	5	2	**2**	2	2
d_{x2}^*	8	8	5	5	5	**5**	5	6
x*1	2	2	5	5	4.18	**3.38**	3.67	2.67
x*2	8	8	5	5	5.82	**6.62**	6.33	7.33
MEA_ineffx1	0	0	0	0.5	0.58	**0.58**	0.48	0.33
MEA_ineffx2	0.33	0	0	0	0.27	**0.45**	0.30	0.27
MEA_effx1	1	1	1	0.5	0.42	**0.42**	0.52	0.67
MEA_eff2	0.67	1	1	1	0.73	**0.55**	0.70	0.733
Agg_MEA	0.83	1	1	0.75	0.57	**0.49**	0.61	0.70
DEA_eff	1	1	1	1	0.65	**0.50**	0.64	0.70

λ denotes the weight of the peers, peer1 denotes the target firm of input X_1 likewise peer2 denotes the target firm of input X_2, X_1 excess is the excess units of input X_1 used, X_2 excess is the excess units of input X_2 used, MEA_ineffx1 & MEA_ineffx2 are the MEA inefficiency score for each input respectively, MEA_effx1 & MEA_effx2 are the MEA efficiency scores for each input respectively, Agg_MEA denotes the aggregated MEA input efficiency score, DEA_eff is the DEA aggregated input-oriented.

From Table 4.3, units A, B, C and D are DEA fully efficient even though units A and D are weakly inefficient (contain non-radial slacks), as a result, only units B and C are MEA fully efficient. Unit A is 83% MEA efficient with 33% MEA inefficiency in utilizing input X_2. For unit D, due to the input-specific inefficiencies of input X_1, its overall MEA efficiency score is 25% (1 – 0.75) less than its DEA efficiency. With the exception of units B and C, the MEA model identified non-radial slacks which could not be with the DEA model. MEA chooses better benchmarks and identifies all possible slacks in its efficiency computation and benchmark selection.

The inputs of units B and C are chosen as peers for the inefficient firms. For input X_1 of units A and F, unit B is chosen as a peer, whereas unit C is chosen as a peer for the same input of units D, E, G and H. The MEA model chose unit C as the peer for input X_2 of units E, F, G and H. The coordinates of the potential improvement points of the inefficient inputs are the appropriate quantity of each input to be used by the inefficient units to be efficient.

8 hypothetical insurers are considered which uses 2 inputs (X_1, X_2) to generate 1 desirable output (Y) and 1 undesirable output C. Table 4.4 contains the hypothetical data, the MEA efficiency scores and lambdas.

From Table 4.4, units A, B, C, D, G and H are fully efficient, hence the MEA variable-specific inefficiency score for all their variables is zero. These units efficiently utilised inputs and produced the maximum amount of desirable output but the minimum amount of its undesirable output. The zero-beta score of these efficient units reveals the absence of contraction (expansion) in the inputs/undesirable outputs (desirable outputs).

There are two inefficient units, E and F in Table 4.4. Both with an MEA comprehensive efficiency of 65%. These inefficient units are more efficient with input X_2 (E = 94% and F = 75%) than with X_1 (E = 77% and F = 65%). Unit E is more efficient with its inputs (X_1 = 77%, X_2 = 94%) than with its desirable outputs (65%) unit F is more efficient with its outputs (Y = 92%, C = 96%) than with its inputs (X_1 = 64%, X_2 = 75%).

Table 4.4. MEA non-oriented efficiency scores of hypothetical firms with undesirable output.

		A	B	C	D	E	F	G	H
Hypothetical data	X_1	2	2	5	10	10	8	7	4
	X_2	12	8	5	5	8	12	9	10
	Y	10	8	9	20	4	10	6	9
	C	7	9	7	10	6	7	5	6
Peers	β	0	0	0	0	0.5	0.49	0	0
	Peer1	A	B	C	D	C	C	G	H
	Peer2	NA	NA	NA	NA	G	D	NA	NA
	Peer3	NA	NA	NA	NA	NA	G	NA	NA
	Peer4	NA	NA	NA	NA	NA	H	NA	NA
Lambda	λ_A	1	0	0	0	0	0	0	0
	λ_B	0	1	0	0	0	0	0	0
	λ_C	0	0	1	0	0.38	0.02	0	0
	λ_D	0	0	0	1	0	0.17	0	0
	λ_E	0	0	0	0	0	0	0	0
	λ_F	0	0	0	0	0	0	0	0
	λ_G	0	0	0	0	0.63	0.01	1	0
	λ_H	0	0	0	0	0	0.80	0	1
Ideal reference	d_{x1}^*	2	2	5	10	5.3	2	7	4
	d_{x2}^*	12	8	5	5	7	5.92	9	10
	d_y^*	10	8	9	20	8.58	11.75	6	9
	d_c^*	7	9	7	10	5.5	6.36	5	6
Potential improvement	x*1	2	2	5	10	7.67	5.08	7	4
	x*2	12	8	5	5	7.50	9.05	9	10
	y*	10	8	9	20	6.29	10.85	6	9
	c*	7	9	7	10	5.75	6.69	5	6
MEA inefficiency	MEA_INEFFx1	0	0	0	0	0.23	0.36	0	0
	MEA_INEFFx2	0	0	0	0	0.06	0.25	0	0
	MEA_INEFFy	0	0	0	0	0.57	0.09	0	0
	MEA_INEFFc	0	0	0	0	0.04	0.04	0	0
MEA efficiency	MEA_x1	1	1	1	1	0.77	0.64	1	1
	MEA_x2	1	1	1	1	0.94	0.75	1	1
	MEA_y	1	1	1	1	0.64	0.92	1	1
	MEA_c	1	1	1	1	0.96	0.96	1	1
Overall MEA	OCMEA	1	1	1	1	0.65	0.65	1	1

λ denotes the weight of the peers, peer1 denotes the target firm of input X_1 likewise peer2 denotes the target firm of input X_2, X_1 excess is the excess units of input X_1 used, X_2 excess is the excess units of input X_2 used, MEA_ineffx1 & MEA_ineffx2 are the MEA inefficiency score for each input respectively, MEA_effx1 & MEA_effx2 are the MEA efficiency scores for each input respectively, Agg_MEA denotes the aggregated MEA input efficiency score, DEA_eff is the DEA aggregated input-oriented.

Further observation reveals that all the efficient units are peers for themselves whereas the inefficient units have either 2 or 4 peers (units C, D, G and H). From Table 4.4, unit E will operate efficiently when it uses 7.67 units of input X_1 and 3.3 units of input X_2 while producing 3.5 units of the desirable output and 3.7 units of the undesirable output. Unit F on the other hand, needs to produce 10.31 units of the desirable output and 6.15 units of the undesirable output using 5.08 units of input X_1 and 9.05 units of inputs X_2.

4.3 Analysis of study data

4.3.1 Descriptive statistics of study data

As stated in the previous chapter, the data for this study was obtained from the annual financial reports submitted to NIC from 2008 to 2019. Thirteen life insurers and seventeen non-life insurers were used due to data availability. The choice of the study's inputs and outputs variables were dependent on the value-added approach while giving attention to existing literature. Three inputs were used namely fixed assets, labour and equity capital. The study considered its outputs to be either desirable or undesirable, choosing two desirable outputs; net premium, investment income and one undesirable output claims. The mean, maximum, minimum and standard deviation of the pooled and grouped data were used as basic descriptive measures in this section. The descriptive statistics of the study's inputs and outputs are presented in Table 4.5. In addition, the test of the difference between the insurance groups and the data values over the 12-year study period are also presented in Table 4.5.

This study used the maximum and minimum values in the descriptive statistics to derive the range. The standard deviation on the other hand shows the spread of the data values for each variable. The number of samples for each variable was added to the descriptive table to show the total number of data points sampled for each variable within the study period as well as the

Table 4.5: Descriptive statistics of input/output (pooled data and business type, 2008 - 2019)

All monetary values are in GHS

		Fixed capital X1	Labour X2	Equity capital X3	Net premium Y1	Investment income Y2	Claims C1
Pooled	Count	360	360	360	360	360	360
	Mean	4920182	14340536	28640604	31835053	9223024	13885505
	Std Dev	8443171	47262441	44835844	53498534	19289031	25518283
	Min	12664	6425	16874	361428	17285	36212
	Max	97518606	873230010	397215400	416881000	132015000	211855714
Time difference	F-statistics	46.45***	2.225	33.75***	57.7***	5.326*	9.745**
Business type groupings							
Life	Count	156	156	156	156	156	156
	Mean	4137251	11572050	27217164	43804573	9223024	20336154
	SD	6574524	14033169	40311535	75200414	19813382	35465612
	Max	42544569	68561000	220703000	416881000	94960139	211855714
	Min	12664	6425	211551	457873	37387	42728
Non-life	Count	204	204	204	204	204	204
	Mean	5518894	16457613	29729118	22681891	7008989	8952656
	SD	9603867	61559293	48078595	23437303	18624616	11609174
	Max	97518606	873230010	397215400	111847000	132015000	60889727
	Min	22648	96064	16874	361428	17285	36212
Group means	T-statistic	-1.618	-1.0969	-0.5387	3.3848**	2.5087**	3.8542***

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001; N/S – not statistically significant; Min, Max and SD mean minimum, maximum and standard deviation respectively.*

number of sample data points sampled from each of the two insurance groups- life and non-life. The equality in the number of samples for each variable confirms the type of panel data chosen for this study- balanced data panel.

In Table 4.5, the standard deviation exceeds the mean values of all the inputs and outputs, which signifies the varying size of insurers operating in Ghana. This is to say, insurers operating in Ghana vary in the size of inputs and outputs used and produced respectively. The extent of deviations from the mean confirms the distinguishing sizes of insurers operating in Ghana. On average, the sampled insurers received GHS28,640,604 from investors as equity capital, invested GHS4,920,182 and GHS14,340,536 into their fixed assets and labour cost respectively. On average, insurers incur a lot on labour related expenses than on acquiring its fixed assets hence, huge differences exist between the average labour cost (M = GHS14,340,536, SD = GHS47,262,441) and the average fixed asset cost (M = GHS4,920,182, SD = GHS8,443,171). In terms of outputs, more was generated from net premiums (GHS31,835,053) compared to investment income (GHS9,223,024) however, the sampled insurers vary on the level of net premiums generated (M = GHS31,835,053, SD = GHS53,498,534). The results of the one-way Anova test of difference in each input and output variable across the entire 12-year study period were significant for all the study's inputs and outputs (except labour). That is to say, there was 0.01%, 1% and 5% significant difference in the amount generated from net premium, claims and investment income respectively across the entire 12-year period. There was also 0.01% significant difference in the resources invested in fixed assets and equity capital across the entire 12-year period.

The sampled non-life insurers were observed to have insignificant higher levels of inputs; labour cost (M = GHS16,457,613; SD = GHS 61,559,293), fixed assets (M = GHS5,518,894; SD = GHS9,603,867) and equity capital (M = GHS29,729,118; SD = GHS48,078,595) than the sampled life insurers (M = GHS11,572,050; SD = GHS14,033,169, M = GHS4,137,251; SD = GHS6,574,524 and M = GHS27,217,164; SD = GHS40,311,535 respectively). However, the sampled life insurers generated significantly larger levels of desired and undesirable outputs; net premium (M = GHS43,804,573; SD = GHS 75,200,414), investment income (M = GHS9,223,024; SD = GHS19,813,382) and claims (M = GHS20,336,154; SD = GHS35,465,612) than non-life insurers (M = GHS 22,681,891; SD = GHS 23,437,303, M = GHS7,008,989; SD = GHS18,624,616 and M = GHS8,952,656; SD = GHS11,609,174 respectively). In line with Ohene-Asare et al. (2019), non-life insurers were shown to have higher levels of operating expenses and equity capital than life insurers. However, these findings were not consistent with the phenomenal growth observed in life businesses than in non-life businesses (Alhassan et al., 2015).

Unlike previous efficiency and dynamic productivity studies that failed to statistically test the nature of returns to scale (Alhassan & Ohene-Asare, 2016; Asmild et al., 2016; Lozano & Soltani, 2020; Ohene-Asare et al., 2019), the RTS technology of the Ghanaian insurance industry is tested following Mahlberg and Url (2010), Ohene-Asare et al. (2017) and Tortosa-Ausina et al. (2012) to avoid biased and misleading conclusions on the efficiency scores (Dyson et al., 2001; Simar & Wilson, 2002). The three different RTS tests of Simar and Wilson (2002 & 2011) (mean of ratios, ratio of means and mean of ratios minus 1) are performed to determine the appropriate RTS technology for the Ghanaian insurance industry. The null hypothesis (H_0) of all the three tests states that the production technology is globally CRS. Tables 4.6 presents the test statistics and the critical values of these tests.

Table 4.6: Tests of returns to scale

$H_0: \psi$ is CRS	Significance level	Mean of ratios $\hat{S}_1$	Ratio of means $\hat{S}_2$	Mean of ratios minus 1 $\hat{S}_3$	Conclusion
Test statistic		0.9442	0.9477	-0.0142	Fail to reject CRS
Critical Value	5%	0.6610	0.7294	-0.0369	Fail to reject CRS
	1%	0.5430	0.5257	-0.0534	Fail to reject CRS

From Table 4.6, the 1% and 5% critical values of the test statistic, $\hat{S}_1$, $\hat{S}_2$ and $\hat{S}_3$ failed to reject the null hypothesis that the production technology is globally CRS. Hence, the production technology of the insurance sector in Ghana is globally CRS. This finding is inconsistent with the large variations among the sampled insurers for this study. However, the RTS assumption chosen by Barros et al. (2008) and (used by) Ansah-Adu et al. (2012) is in line with the RTS technology chosen with the three tests, CRS. Ansah-Adu et al. (2012) posits that CRS is a suitable RTS for the insurance sector in Ghana because the technology satisfies some desirable mathematical properties such as; continuity, (weak) monotonicity, commensurability and relatively easy accessibility and interpretation. The returns to scale of the Ghanaian insurance industry can be attributable to any returns to scale however, this study uses the RTS technology chosen with the three tests and concludes that the Ghanaian insurance sector does not vary in size.

In order to validate the MEA assessment, the study conducted an isotonicity test which entails the computation of all inter-correlations of all inputs and outputs (Avkiran, 1999; Wanke et al., 2015). The variables are said to be isotonic when a significant Pearson's correlation coefficient exists between an input and an output which shows that an increase in an input is highly related to an increase in an output. The correlation matrix in Table 4.7 shows that the isotonicity property of the variables are confirmed at the 0.1% significant level.

Table 4.7: Correlation of input and output variables.

	Fixed capital	Labour	Equity capital	Net premium	Investment income	Claims
Fixed capital	1					
Labour	0.13*	1				
Equity capital	0.50***	0.16**	1			
Net premium	0.42***	0.21***	0.56***	1		
Investment income	0.19***	0.23***	0.47***	0.61***	1	
Claims	0.36***	0.18**	0.50***	0.90***	0.56***	1

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001*

4.3.2 Findings for claims as undesirable output

To the best of the author's knowledge, only one insurance efficiency study has considered claims as an undesirable output (Reyna & Fuentes, 2018). Still, the exclusion of undesirable outputs in insurance efficiency analysis may lead to misleading results. To that end, our first objective is to mathematically model claims as an undesirable output using the MEA model and to compare the efficiency estimates between claims as desirable and undesirable output. In line with Bi et al. (2014) and Reyna and Fuentes (2018), the three axioms of undesirable outputs postulated by Fare et al. (2005) were adopted. The MEA average efficiency estimates for claims as desirable and undesirable outputs are presented in Table 4.8. Table 4.8 also shows the number of times insurers were efficient on claims and the corresponding efficiency percentage for the study period. Appendices B and D present the claims efficiencies when claims were used as a desirable and undesirable output respectively. In all of our analysis, we use the combined meta-analysis, where all the observations from all the years (2008-2019) are measured against a common meta frontier and then classified across time, firms and groups for further analysis. This makes comparisons feasible and practical since their MEA efficiency scores were measured relative to a common pooled frontier.

Enterprise Life (Enter L) scored the highest (99%) on claim efficiency whereas Met Life scored the second highest (98%) when claims were considered as an undesirable output. However, these efficiency scores changed when claims were considered as a desirable output (Met Life - 100%, Enterprise Life – 87%). Besides, the average insurer recorded lower efficiency scores when claims were considered as a desirable than an undesirable. This implies that had we used claims as a desirable output, misleading results could have emerged. Another potentially practical justification for considering claims as an undesirable output emanates from the rankings of the efficiency scores. Specifically, the rankings of 21 out of 30 insurers changed between the two models (desirable and undesirable claims). Star Life (Star L) for instance, was ranked 5th when claims were considered as an undesirable output but ranked 2nd when claims were considered as a desirable output. Glico Life (Glico L) which was ranked 9th (least ranked) when claims were undesirable was ranked 6th when claims were desirable. These findings suggest that the claims efficiency could be underestimated or overestimated depending on whether it was considered as a desirable or an undesirable. Comparing desirable claims efficiency with undesirable claims efficiency revealed that, on average, the insurers were 88%

Table 4.8: Average claims efficiency scores (and rankings) for claims as a desirable and an undesirable output (2008 - 2019)

	Claims as an undesirable output				Claims as a desirable output			
Insurer	**Claims Efficiency**	**No. of efficient claims out of 12**	**Percentage of times efficient**	**Rank**	**Claims Efficiency**	**No. of efficient claims out of 12**	**Percentage of times efficient**	**Rank**
Activa I	0.83	1	8.30%	9th	0.37	1	8.33%	8th
CDH L	0.76	1	8.30%	9th	0.51	0	0.00%	
Donewell IC	0.84	2	16.70%	8th	0.46	1	8.33%	8th
Donewell L	0.87	5	41.70%	5th	0.75	5	41.67%	5th
Enter L	**0.99**	**10**	**83.30%**	**2nd**	**0.87**	**7**	**58.33%**	**3rd**
Enterprise IC	0.85	5	41.70%	5th	0.81	5	41.67%	5th
Equity IC	0.93	6	50.00%	4th	0.40	0	0.00%	
Ghana L	0.84	5	41.70%	5th	0.65	3	25.00%	6th
Ghana UA	0.79	1	8.30%	9th	0.61	1	8.33%	8th
GhanaUnion L	0.95	5	41.70%	5th	0.44	0	0.00%	
Glico GI	0.78	1	8.30%	9th	0.55	0	0.00%	
Glico L	**0.82**	**1**	**8.30%**	**9th**	**0.85**	**3**	**25.00%**	**6th**
Met L	**0.98**	**11**	**91.70%**	**1st**	**1.00**	**12**	**100.00%**	**1st**
Metropolitan IC	0.83	2	16.70%	8th	0.80	3	25.00%	6th
NSIA GC	0.86	3	25.00%	7th	0.33	0	0.00%	
Phoenix IC	0.86	0	0.00%		0.57	0	0.00%	
Phoenix L	0.87	6	50.00%	4th	0.75	6	50.00%	4th
Prime I	0.82	4	33.30%	6th	0.30	0	0.00%	
Provident IC	0.83	1	8.30%	9th	0.30	0	0.00%	
Provident L	0.91	5	41.70%	6th	0.87	5	41.67%	5th
Quality IC	0.84	0	0.00%		0.42	0	0.00%	
Quality L	0.86	3	25.00%	7th	0.70	2	16.67%	7th

Regency AI	0.92	5	41.70%	5th	0.54	2	16.67%	7th
SIC IC	0.79	1	8.30%	9th	0.33	0	0.00%	
SIC L	0.90	8	66.70%	3rd	0.94	8	66.67%	2nd
Star AC	0.92	3	25.00%	7th	0.59	2	16.67%	7th
Star L	**0.89**	**5**	**41.70%**	**5th**	**0.95**	**8**	**66.67%**	**2nd**
Unique IC	0.82	4	33.30%	6th	0.51	2	16.67%	7th
Vanguard AC	0.9	3	25.00%	7th	0.80	3	25.00%	6th
Vanguard L	0.93	8	66.70%	3rd	0.83	8	66.67%	2nd
Mean	**0.87**				**0.67**			
Median	**0.88**				**0.66**			
SD	**0.12**				**0.28**			
Min	**0.40**				**0.02**			
Max	**1**				**1**			
Count	**360**				**360**			
Test of means	**T-test**	**13.351*** **						
	Wilcoxon test	**45230*** **						

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001; Min, Max and SD mean minimum, maximum and standard deviation respectively.*

efficient under undesirable claims efficiency, but 66% efficient under desirable claims efficiency. To test for the significant difference in the ranks rather than averages of efficiency between undesirable claims efficiency and desirable claims efficiency, the non-parametric Wilcoxon sign-ranked test was used and corroborated with the dependent t-test (parametric test). The p-value (0.00) of the Wilcoxon sign-ranked test statistic (W = 45230) confirmed a significant difference between the rankings of desirable and undesirable claims efficiency estimates at 0.1% level of significance.

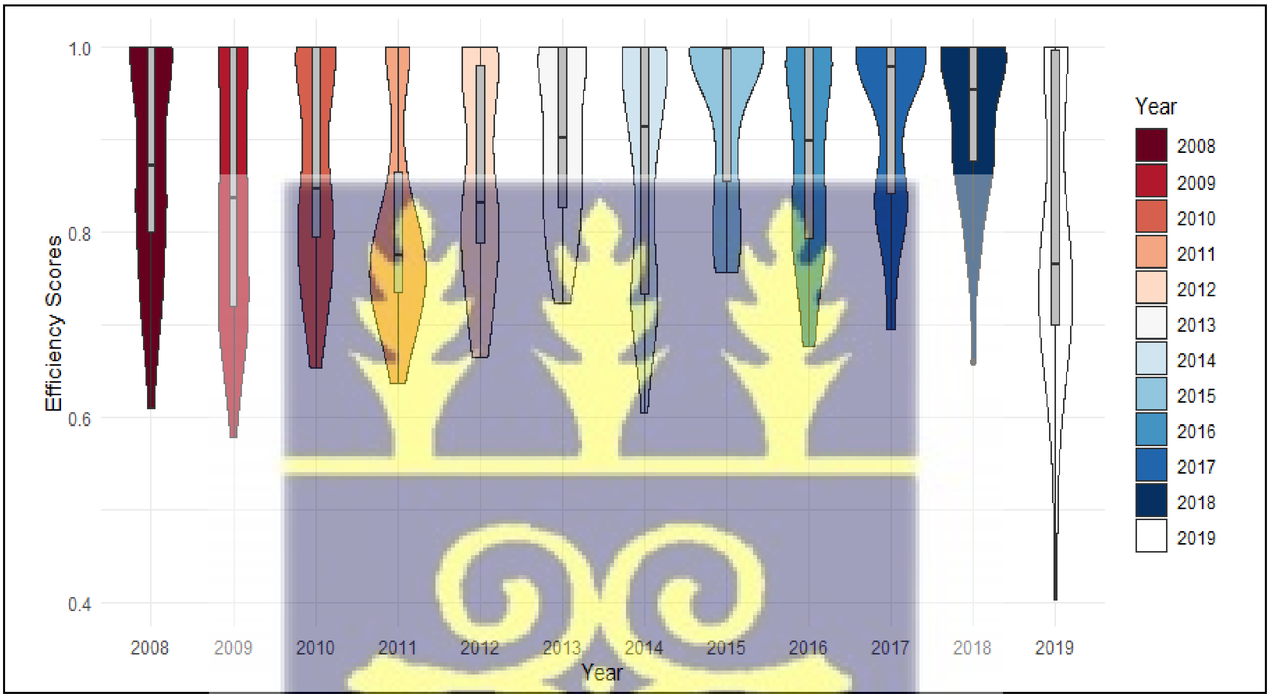


Figure 4.3: Claim efficiency for insurers across the years

With the confirmed significant difference between the rankings of the two efficiencies, this study considers claims as an undesirable output. The violin plot is used in Figure 4.3 to illustrate the distribution of the claims efficiencies across the 12-year period. A violin plot is used instead of kernel density graphs or box plots because it presents a five-point summary of the claim efficiency estimates in addition to the distribution of the efficiency estimates (Färe et al., 2015; Liu et al., 2021). Besides, the density traces of the violin plot provide new information on the shape of the distribution for the claims efficiencies (Hintze & Nelson, 1998). From Figure 4.3, the same median efficiency (the thick black line in the inter-quartile range of the boxplot) was the same for 2016 and 2013, even though fatter densities were illustrated in 2013. Notably, different proportions of insurers were shown to have obtained full efficiency in a year. In 2019 and 2011, a relatively small proportion of the insurers operated at full claim efficiency even though a relatively greater proportion of the insurers attained full claims efficiency in 2015, 2017 and 2018. Unlike the maximum claims efficiencies which remained stable across the entire sample period, the minimum claims efficiency varied across the years. In 2019, the lowest minimum claim efficiency was shown to be obtained by some insurers with the highest minimum claim efficiency recorded in 2015. The thin densities of the claim distribution in 2019, signifies the poor performance of most of the insurers in that year. The fatter densities, highest minimum claim efficiency and the shorter claim efficiency signify the good performance of the sampled insurers in 2013 and 2015.

4.3.3 Variable-specific efficiency scores

Consistent with Asmild and Matthews (2012) and other studies, arguably, a particular insurer can be doing better in claims than in another input, say, labour or another output, say, net premiums. Thus, there is the need to be able to select benchmarks such that, the non-radial adjustments to the inputs and outputs correspond to the potential improvements identified. This said, this study's second objective is to assess the input/output-specific efficiencies of Ghanaian insurers in a disaggregated view. The average comprehensive and variable-specific efficiency scores for each insurer are assessed and presented in Table 4.9. Appendices C and D present the comprehensive and variable-specific efficiencies respectively. As indicated, the 12-year data for the insurers are pooled, implying that the same insurer in different periods is considered as a different observation under evaluation. Using a common frontier rather than

Table 4.9: Average efficiency of insurers for pooled data (2008 – 2019).

Insurers	Fixed Asset	Labour	Equity Capital	Net Premium	Investment Income	Claims	Comprehensive Efficiency
Activa I	0.80	0.79	0.79	0.75	0.24	0.83	0.31
CDH L	0.67	0.74	0.73	0.71	0.21	0.76	**0.19**
Donewell IC	0.74	0.80	0.82	0.81	0.44	0.84	0.37
Donewell L	0.82	0.84	0.84	0.74	0.46	0.87	0.51
Enter L	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**	**0.99**	**0.96**
Enterprise IC	0.83	0.86	0.82	0.86	0.45	0.85	0.41
Equity IC	0.87	0.88	0.88	0.95	0.72	0.93	0.61
Ghana L	0.78	0.82	0.84	0.74	0.46	0.84	0.50
Ghana UA	0.71	0.78	**0.69**	0.67	0.37	0.79	0.35
GhanaUnion L	0.91	0.88	0.87	0.97	0.88	0.95	0.75
Glico GI	0.71	0.74	0.73	0.73	0.23	0.78	0.32
Glico L	0.84	0.86	0.75	0.87	0.38	0.82	0.41
Met L	0.99	0.99	0.98	0.94	1.00	0.98	0.96
Metropolitan IC	0.81	0.80	0.81	0.80	0.38	0.83	0.47
NSIA GC	0.80	0.80	0.81	0.74	0.48	0.86	0.41
Phoenix IC	0.81	0.80	0.82	0.86	0.35	0.86	0.36
Phoenix L	0.89	0.87	0.89	0.87	0.57	0.87	0.62
Prime I	0.75	0.77	0.78	**0.61**	0.24	0.82	0.28
Provident IC	0.72	0.77	0.77	0.76	0.22	0.83	0.28
Provident L	0.86	0.88	0.86	0.73	0.91	0.91	0.71
Quality IC	0.70	0.76	0.80	0.84	0.27	0.84	0.29
Quality L	0.77	0.83	0.86	0.81	0.69	0.86	0.53
Regency AI	0.91	0.87	0.92	0.93	0.49	0.92	0.62
SIC IC	**0.67**	**0.72**	0.71	0.72	**0.19**	0.79	0.19
SIC L	**0.87**	**0.91**	**0.91**	**0.99**	**0.82**	**0.90**	**0.67**
Star AC	0.88	0.85	0.84	0.89	0.61	0.92	0.66
Star L	0.86	0.90	0.92	0.95	0.64	0.89	0.69
Unique IC	0.82	0.80	0.84	0.86	0.36	0.82	0.42
Vanguard AC	0.88	0.83	0.89	0.89	0.44	0.90	0.58
Vanguard L	0.94	0.91	0.94	0.94	0.82	0.93	0.84
Mean	**0.82**	**0.84**	**0.84**	**0.83**	0.51	**0.87**	**0.82**
Median	**0.09**	**0.07**	0.08	0.10	**0.25**	**0.06**	**0.09**
SD	**0.82**	**0.83**	**0.84**	**0.85**	**0.45**	**0.86**	**0.82**
Min	**0.67**	0.72	**0.69**	**0.61**	**0.19**	0.76	**0.67**
Max	**0.99**	**0.99**	**0.99**	**1.00**	**1.00**	**0.99**	**0.99**
Count	**30**	**30**	**30**	**30**	**30**	**30**	**30**

Min, Max and SD mean minimum, maximum and standard deviation respectively.

separate yearly frontiers ensure comparability of efficiency scores and identification of rising and falling trends in efficiency. Included in the Table are the summary statistics of efficiency scores across insurers for each variable and for comprehensive MEA efficiency scores. The geometric mean efficiencies are estimated because the arithmetic means could give misleading conclusions when used to summarise normalised benchmark scores (Ohene-Asare & Asmild, 2012; Roberts, 1990).

We start with the comprehensive MEA efficiency scores in Table 4.9 and Figure 4.4. The highest and lowest comprehensive MEA efficiency scores of insurers are shown to be 99% and 67% respectively. On average, insurers recorded a full efficiency of 82%. The findings clarify that larger parts of insurers' variables are performing MEA efficiently on the combined variables in the insurance sector as efficiency scores are more than 50% generally. This implies that there is less potential to cut inputs and undesirable outputs or raise desirable outputs. Having said that, investment income inefficiency is the main driver of comprehensive MEA inefficiency as evidenced in Figure 4.4. It is observed that the average aggregated or integrated MEA efficiencies and investment income efficiencies are generally lower than those of the other variable-specific efficiency scores across insurance firms. The lower comprehensive efficiencies appear to be emanating from the lower efficiencies on investment income since both efficiencies follow the same pattern.

To get a disaggregated view of the efficiencies, the variable-specific efficiency scores are examined. The highest fixed assets-specific, labour-specific, equity capital-specific, net premium-specific, investment income-specific and claims-specific efficiency scores (99%, 99%, 100%,100%,99%,96% respectively) are shown to be obtained by Enterprise Life (Enter L), the oldest foreign insurer in Ghana. This suggests that Enterprise Life, is the best insurer at utilising inputs (fixed assets, labour and equity capital) and at generating outputs (net premium, investment income and claims) in an efficient way. Hence, they could only improve their fixed asset and labour cost by 1%, their investment income and claims by 1% and 4% respectively. On average, SIC Insurance Company is shown to be the worst performing insurer on the fixed asset, labour and investment income (67%, 72% and 19% respectively). The lowest average efficiency for equity capital, net premium and claims were recorded by Ghana Union Assurance (Ghana UA), Prime Insurance (Prime I) and CDH Life (CDH L) respectively (69%, 61% and 76%). In terms of outputs (net premium, investment income and claims), Prime Insurance, SIC Insurance Company and CDH Life could improve its net premium-specific, investment income-specific and claims-specific efficiency by 39%, 81% and 34% respectively.

By disaggregating, insurers are generally observed to be performing well on the variable-specific efficiency scores (except investment income) compared to the average comprehensive MEA efficiencies. For instance, the variable-specific efficiencies of SIC Life was between 99% and 80%, whereas its integrated efficiency score was 67%, confirming the misleading results that comprehensive MEA efficiency scores can produce.

Figure 4.5 depicts the violin plots for the disaggregated efficiency scores. The violin plot, as noted, reveals the five-point summary of the efficiency scores and also estimates the density function of the efficiency scores (Färe et al., 2015; Liu et al., 2021). Except for investment income efficiency distribution, a similar spread and distributional pattern are shown for all the variables. This confirms the lower average efficiencies recorded on investment income across the years. Claims are shown to have the fattest density followed by labour and equity capital. The relatively small spread on the claims' efficiency density reveals the higher efficiencies recorded by insurers. The wider spread in net premium efficiency distribution coupled with

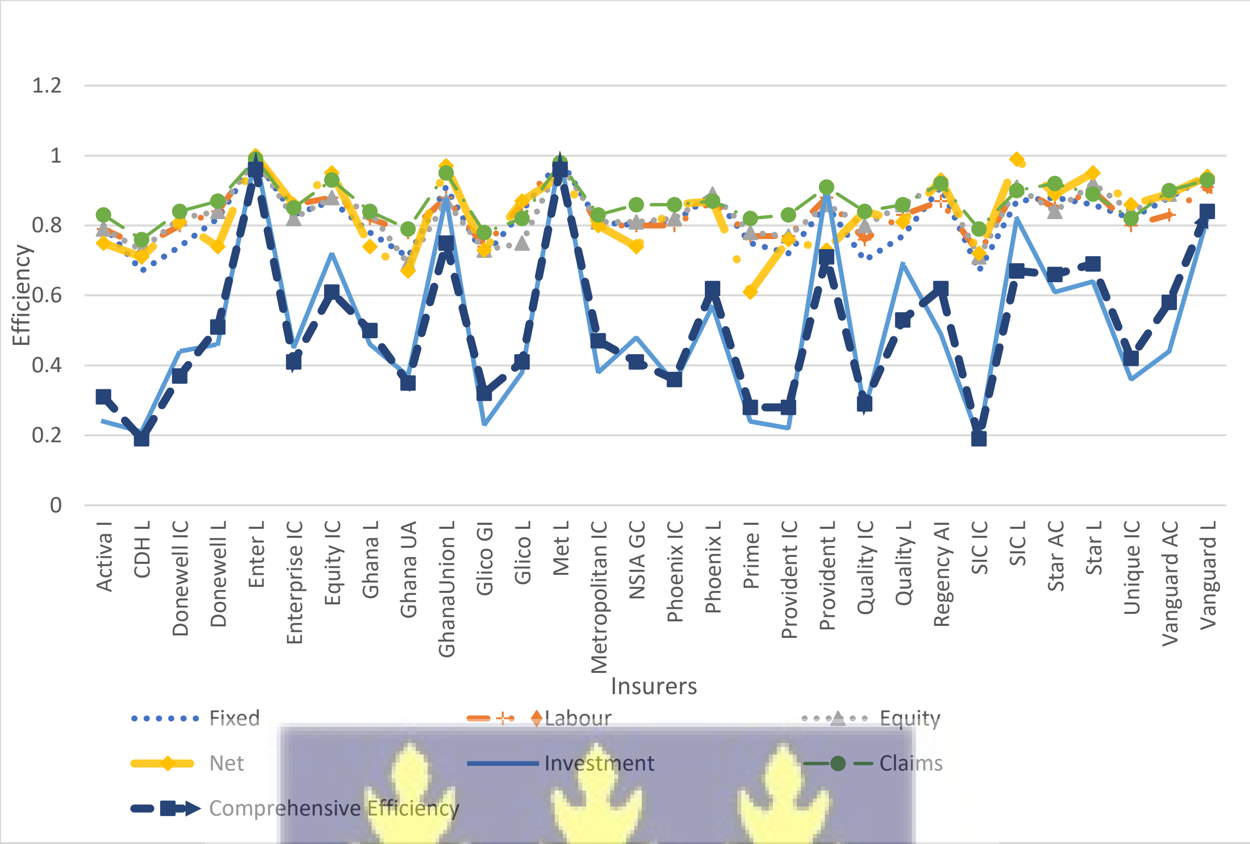


Figure 4.4: Average variable-specific and comprehensive efficiencies across insurers (2008 – 2019)

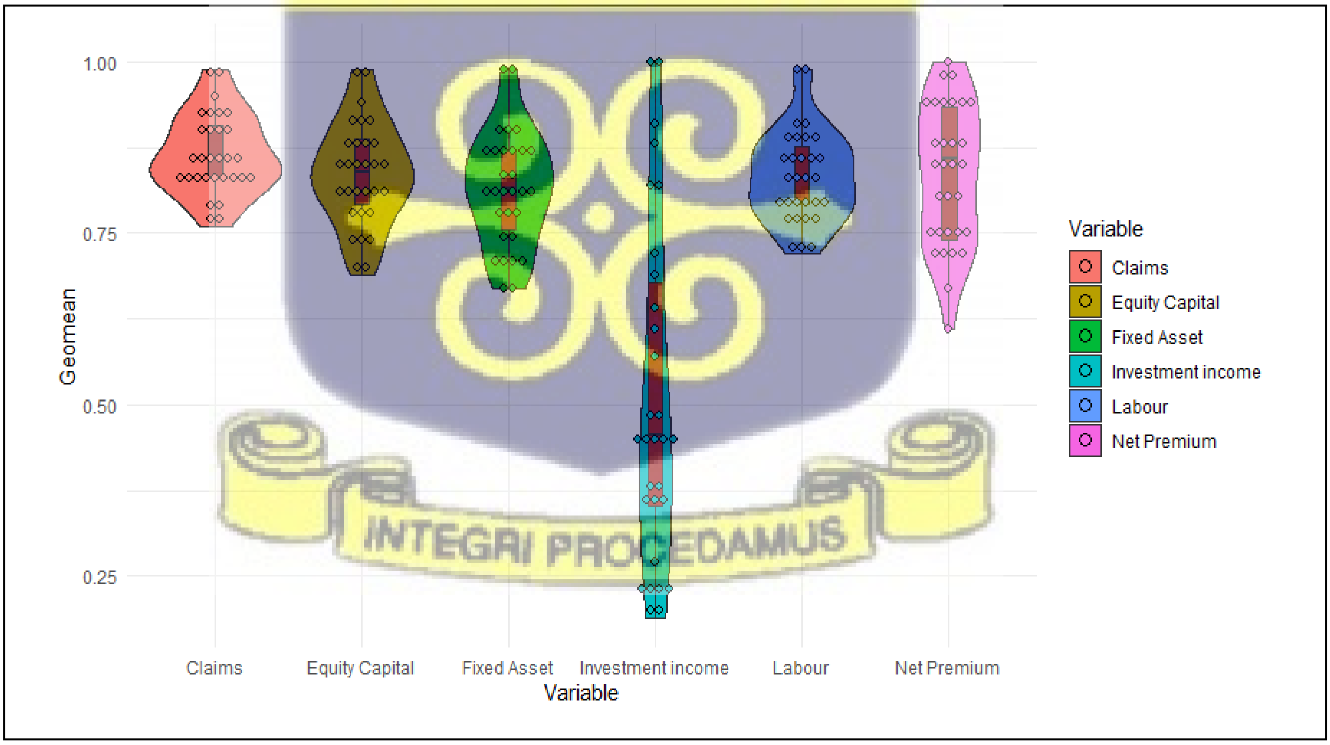


Figure 4.5: Variable-specific efficiencies (2008 – 2019)

their thin densities reveal the relatively lower efficiencies recorded by some insurers. Overall, insurers are shown to have performed well on all the variables except investment income.

To further assess the trends and patterns over time in disaggregated and aggregated efficiencies, the average variable-specific and comprehensive efficiencies of the insurers across the study period are shown in Table 4.10. As indicated, using the aggregated or comprehensive efficiency

Table 4.10: Average variable-specific efficiencies across time (2008 – 2019).

Year	Fixed Asset	Labour	Equity Capital	Net Premium	Investment Income	Claims	Comprehensive Efficiency
2008	0.84	0.88	0.86	0.83	0.19	0.87	**0.26**
2009	0.82	0.82	0.85	0.81	0.17	0.83	**0.25**
2010	0.81	0.83	0.85	0.84	**0.11**	0.86	**0.17**
2011	0.77	0.79	0.79	**0.71**	0.31	0.80	**0.37**
2012	0.77	**0.78**	0.83	0.81	0.54	0.85	0.54
2013	0.81	0.84	0.88	0.89	0.60	0.89	0.64
2014	0.81	0.81	0.78	0.82	0.70	0.87	0.64
2015	**0.91**	**0.90**	**0.89**	0.89	0.77	**0.92**	0.76
2016	0.78	0.83	0.78	0.84	0.61	0.88	0.59
2017	0.85	0.88	**0.89**	**0.90**	**0.76**	**0.92**	0.74
2018	0.85	0.85	0.84	0.87	0.65	**0.92**	0.66
2019	0.78	0.80	**0.77**	0.72	0.57	**0.79**	**0.52**
Mean	**0.82**	**0.83**	**0.83**	**0.83**	**0.50**	**0.87**	**0.51**
Test of difference (Friedman Test)	**42.07*****	**37.451*****	**37.45*****	**48.023*****	**71.463*****	**45.302*****	**69.91*****

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001*

scores alone to depict efficiency levels and changing trends, we are unable to fully understand the true sources of inefficiencies and to determine the patterns and trends of efficiency differences, which are useful for managerial and regulatory policy making. Hence, the use of the disaggregated scores. Whereas the highest average fixed asset-specific and labour-specific was obtained in 2015, the highest investment income-specific and net premium-specific was also obtained in 2017. Unlike these variables, the highest equity capital-specific efficiency was obtained in two different years, 2015 and 2017, with the highest claims-specific efficiency, also recorded in these years including 2018. Labour recorded the lowest average efficiency in

2012, equity capital and claims recorded the lowest efficiency in 2019, whereas net premium and investment income recorded the lowest average efficiency in 2011 and 2010 respectively. These revealed that insurers generally utilised all inputs to generate more investment income with few claim payments in 2015. In comparison, with the targets, some inputs were not properly utilised in 2019 (equity capital), 2011 and 2012 (fixed asset and labour respectively).

Once again, from Table 4.10, it is observed that the comprehensive efficiency scores were generally below that of the individual variable-specific MEA efficiency scores. For instance, the comprehensive efficiency scores from 2008 and 2011, were all below 50% whereas the variable-specific scores were all above 50% for the same period. Claims recorded efficiency scores 79% and above over the study period, which shows its remarkable contributions towards overall performance. The highest average annual mean efficiency came from claim efficiency (87%), followed by labour efficiency (83%), equity capital (83%) and net premium efficiency (83%), then fixed assets (82%) and investment income (50%). This can be confirmed from the line graphs in Figure 4.6. To test if significant difference exists in the different groups of annual variable-specific efficiency means, a nonparametric Friedman test is performed. Yet, recall that the test is based on rank comparison instead of averages. The results suggest significant difference among the ranks for both aggregated and disaggregated efficiencies at 0.1% significant level.

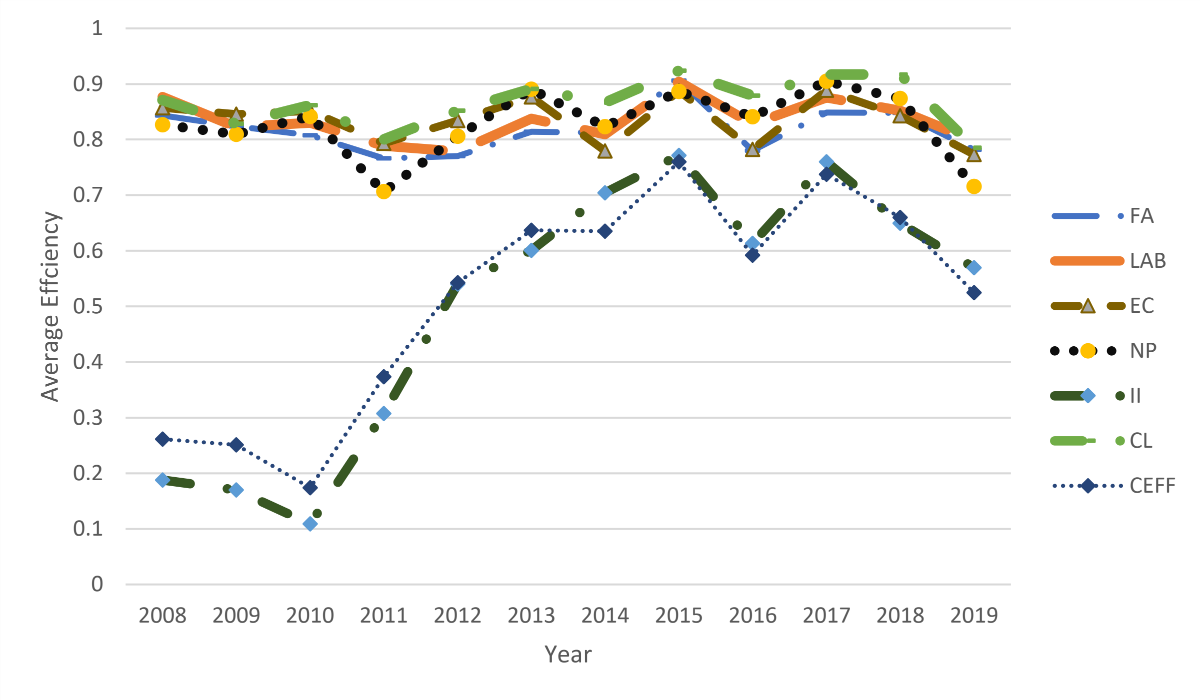


Figure 4.6: Average efficiencies scores over the years (2008 – 2019)

Figure 4.6 provides additional insights into the annual variable-specific (disaggregated) and aggregated efficiencies across the entire study period. The variable-specific efficiency patterns for each variable (except investment income) are observed to be relatively stable as time passed. Still investment income efficiency scores were observed to be substantially increasing during 2008-2019 periods. However, efficiencies for the variables are observed to be slowly declining after 2018. This reveals an equal level of performance on these variables across the years, except for 2018. Again, the average comprehensive MEA efficiencies and investment income efficiencies are generally lower than those of the other variable-specific scores. This showed investment income inefficiency to be a strong contributor to the overall MEA inefficiency. The substantial increase in efficiency levels across the study period reveals an improvement in performance on investment income and insurer performance at large. Unlike the other variables, a sharp decrease in investment income efficiency is observed from 2017. Again, investment income and comprehensive efficiency are revealed to be related and to follow the same trends and patterns.

4.3.4 Life and non-life efficiencies

There exist unconfirmed differences between the efficiency and dynamic productivity of life and non-life insurers in Ghana. Whereas Ohene-Asare et al. (2019) observed significantly lower input productivity growth in Ghanaian life businesses but statistically insignificant differences between the cost productivity growth of the insurance groups, Danquah et al. (2017) observed Ghanaian life insurers to be more cost-efficient than their counterparts, the non-life insurers. This said, our third objective is to assess the comprehensive and variable-specific MEA efficiency differences between life and non-life insurers.

Table 4.11 depicts the pooled meta-analysis of the comprehensive MEA efficiency scores of the life and non-life insurers across the 2008-2019 periods, together with the number of times insurers in a group have been MEA fully efficient in a given year and their percentages. A comparison of the average MEA scores for the life and non-life insurers are pictured as line graphs in Figure 4.7 and as violin plots in Figure 4.8. From Table 4.11, it appears the impact of the 2006 policies and regulations on the separation of insurers into life and non-life insurers became apparent from the years 2010-2011, where we witness increases in integrated efficiency scores in both insurance groups, even though this begun to gradually dip from the year 2017 to 2019. Having said that, we noticed that life insurers (with mean efficiency of 63%) were generally consistently more efficient than their non-life counterparts (with mean efficiency of 44%) over the study period.

Again, judging from Table 4.11 and based on the number of efficient insurers in each group, it can be deduced that life insurers had a relatively higher number of efficient insurers (maximum = 9, minimum = 4) than for non-Life insurers (maximum = 7, minimum = 1) over the study period. Besides, relatively greater percentage of fully efficient life insurers (highest – 69.2%, lowest –

Table 4.11: Comprehensive average efficiency score of life and non-life insurers (2008 – 2019).

	Life				Non-life			
	Efficiency	**No. of efficient firms in the group**	**Percentage**	**Test of difference across years**	**Efficiency**	**No. of efficient firms in the group**	**Percentage**	**Total no. of eff firms out of 30**
2008	0.33	5 out of 13	38.5%	123.5	0.22	**7 out of 17**	41.2%	12
2009	0.38	5 out of 13	38.5%	145	0.18	4 out of 17	23.5%	9
2010	**0.31**	**5 out of 13**	**38.5%**	151	**0.11**	**4 out of 17**	**23.5%**	**9**
2011	**0.62**	**4 out of 13**	**30.8%**	188**	**0.25**	**1 out of 17**	**5.9%**	**5**
2012	0.78	5 out of 13	38.5%	190**	0.41	2 out of 17	11.8%	7
2013	0.80	6 out of 13	46.2%	180**	0.54	3 out of 17	17.6%	9
2014	0.73	6 out of 13	46.2%	151	0.57	3 out of 17	17.6%	9
2015	0.83	**9 out of 13**	**69.2%**	142	0.71	**6 out of 17**	35.3%	**15**
2016	0.59	5 out of 13	38.5%	112	0.59	**4 out of 17**	23.5%	9
2017	**0.79**	**9 out of 13**	**69.2%**	148	**0.70**	**4 out of 17**	**23.5%**	**13**
2018	**0.73**	**7 out of 13**	**53.8%**	147.5	**0.61**	**3 out of 17**	**17.6%**	**10**
2019	**0.70**	**7 out of 13**	**53.8%**	170.5*	**0.42**	**1 out of 17**	**5.9%**	**8**
Mean				**0.63**	**0.44**			
Median				**0.72**	**0.48**			
SD				**0.19**	**0.21**			
Min				**0.31**	**0.11**			
Max				**0.83**	**0.71**			
Non-parametric test (Friedman)				**21224*****				
Parametric test (T-test)				**-5.6726*****				

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001; Min, Max and SD mean minimum, maximum and standard deviation respectively.*

30.8%) were recorded compared with non-life insurers. In 2015, 15 fully efficient insurers were recorded out of which 9 were life insurers and 6 were nonlife insurers. In general, the percentage of the number of efficient life insurers was more than the percentage of the number of efficient non-life insurers. Following the greater percentage of fully efficient sampled insurers in 2015, the number of fully efficient sampled insurers reduced inconsistently each year. Whereas the non-life insurers experienced a quick reduction in the number of fully efficient non-life insurers (6 in 2015, 4 in 2016 and 2017 and 1 in 2019), the number of fully efficient life insurers has been inconsistent (9 in 2015, 5 in 2016, 9 in 2017 and 7 in 2018 and

2019). Hence, the inconsistency in the total number of fully efficient insurers from 2015 to 2019 can be connected to the inconsistencies recorded in the life group. As the number of efficient life insurers increased steadily across the study period, the relative number of nonlife insurers declined speedily. It is clear from Table 4.11 that, based on their median efficiency scores, life insurers (median = 83%) outperformed non-life insurers (median = 52%). Also, the number and the percentage of efficient life insurers are consistently higher than of the number and the percentage of efficient non-life insurers, indicating some potential advantages that life insurers may have. These findings are in line with Alhassan et al. (2015) which identified life insurers to be more DEA efficient than non-life insurers and Ansah-Adu et al. (2012) which also obtained higher DEA efficiency scores for Ghanaian life insurers.

To statistically establish if significant differences exist between the efficiency scores and the rankings of life and non-life insurers, we employ the nonparametric test, the independent Wilcoxon-Mann-Whitney U test, following other studies (Asmild et al., 2019a; Asmild & Matthews, 2012). This is because efficiency scores are nonparametric in nature and hence lack parametric statistical and distributional properties. The findings of the Wilcoxon-Mann-Whitney U test and its corroborated test, the independent t-test, and their corresponding p-values are shown in the bottom half of Table 4.11. The Wilcoxon-Mann-Whitney U test determines if the MEA efficiencies for both life and non-life come from the same distribution. The results show a statistically significant difference between the distribution of the MEA efficiency estimates for the two different insurers during the 2008-2019 periods. This means that based on the pooled data, life insurers significantly outperformed (p-value < 0.001) non-life insurers across the entire study period.

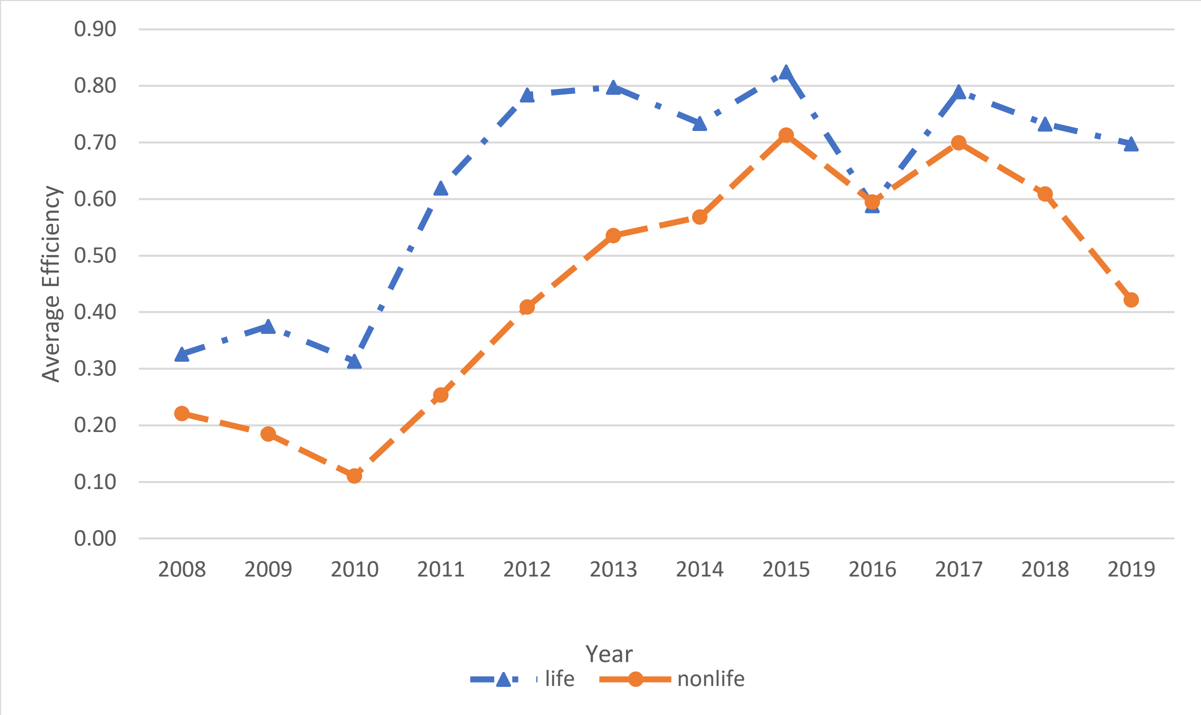


Figure 4.7: Average efficiencies of business groups across years (2008 – 2019)

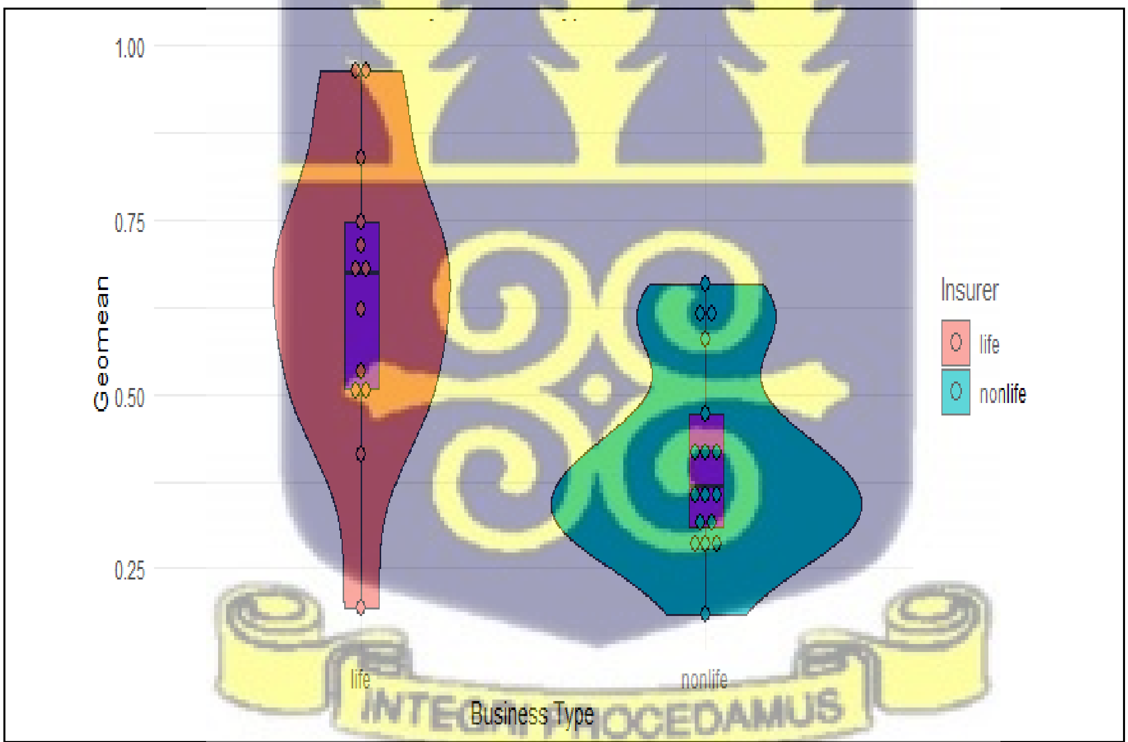


Figure 4.8: Distribution of average efficiency by business types (2008 -2019)

For deeper understanding and concise presentation, violin plots were used to present the summary statistics and the shape of the distribution of the comprehensive MEA efficiency scores of the life and non-life insurers as depicted in Figure 4.8. Already, the line graph in Figure 4.7 showed the average efficiencies of life insurers were consistently above that of non-life insurers over the study period except in 2016 where they equalled each other, a fact that was statistically confirmed by the Mann-Whitney U test. The violin plot, unlike the boxplot or line graph, shows both density estimates of the scores (for the shape of the distribution) and the (basic) five-point summary statistics of efficiency scores with a boxplot (Färe et al., 2015; Hintze & Nelson, 1998; Liu et al., 2021; Richter et al., 2021). The violin plot can portray the presence of clusters in the nonparametric data and the densities can showcase the peaks, bumps and valleys in the distribution. It can combine the merits of the box plots with density traces in one diagram, by making the width of the box proportional to the estimated density (Färe et al., 2015). The plots show unimodality for life and bimodality for non-life insurers integrated efficiencies. More skewness is observed in life than in non-life efficiencies. The violin plots of the efficiencies of life insurers showed fatter densities between 50% and 70% average efficiency level whereas no efficiency densities were shown for non-life insurers beyond 70% average efficiency level. This suggested that whereas a greater percentage of life insurers recorded average comprehensive efficiency above 50%, no non-life insurer recorded average comprehensive efficiency beyond 70%. Further observation reveals a bump in the violin plot of the non-life insurers between 50% and 25% average efficiency suggesting that majority of the non-life insurers recorded comprehensive average efficiency scores between 50% and 25%. Generally, non-life insurers performed poorly than life insurers during the study period.

Table 4.12:Variable-specific efficiencies of life and non-life insurers.

Life Insurers	Fixed Asset (FA)	Labour (LAB)	Equity Capital (EC)	Net Premium (NP)	Investment Income (II)	Claims (CL)
CDH L	**0.67**	**0.74**	**0.73**	**0.71**	**0.21**	**0.76**
Donewell L	0.82	0.84	0.84	0.74	0.46	0.87
Enter L	**0.99**	**0.99**	**0.99**	**1**	**1**	**0.99**
Ghana L	0.78	0.82	0.84	0.74	0.46	0.84
Ghana Union L	0.91	0.88	0.87	0.97	0.88	0.95
Glico L	0.84	0.86	0.75	0.87	0.38	0.82
Met L	**0.99**	**0.99**	0.98	0.94	**1**	0.98
Phoenix L	0.89	0.87	0.89	0.87	0.57	0.87
Provident L	0.86	0.88	0.86	0.73	0.91	0.91
Quality L	0.77	0.83	0.86	0.81	0.69	0.86
SIC L	0.87	0.91	0.91	**0.99**	0.82	0.9
Star L	0.86	0.90	0.92	0.95	0.64	0.89
Vanguard L	0.94	0.91	0.94	0.94	0.82	0.93
Mean	**0.86**	**0.88**	**0.88**	**0.87**	**0.68**	**0.89**
Median	**0.86**	**0.88**	**0.87**	**0.87**	**0.69**	**0.89**
SD	**0.09**	**0.07**	**0.08**	**0.11**	**0.25**	**0.06**
Min	**0.67**	**0.74**	**0.73**	**0.71**	**0.21**	**0.76**
Max	**0.99**	**0.99**	**0.99**	**1**	1	**0.99**
Non-life Insurers						
Activa I	0.8	0.79	0.79	0.75	0.24	0.83
Donewell IC	0.74	0.8	0.82	0.81	0.44	0.84
Enterprise IC	0.83	0.86	0.82	0.86	0.45	0.85
Equity IC	0.87	**0.88**	0.88	**0.95**	**0.72**	**0.93**
Ghana UA	0.71	**0.78**	0.69	0.67	0.37	0.79
Glico GI	0.71	0.74	0.73	0.73	0.23	**0.78**
Metropolitan IC	0.81	0.8	0.81	0.8	0.38	0.83
NSIA GC	0.8	0.8	0.81	0.74	0.48	0.86
Phoenix IC	0.81	0.8	0.82	0.86	0.35	0.86
Prime I	0.75	0.77	0.78	**0.61**	0.24	0.82
Provident IC	0.72	0.77	0.77	0.76	0.22	0.83
Quality IC	0.7	0.76	0.8	0.84	0.27	0.84
Regency AI	**0.91**	0.87	**0.92**	0.93	0.49	0.92
SIC IC	**0.67**	**0.72**	0.71	0.72	**0.19**	0.79
Star AC	0.88	0.85	0.84	0.89	0.61	0.92
Unique IC	0.82	0.8	0.84	0.86	0.36	0.82
Vanguard AC	0.88	0.83	0.89	0.89	0.44	0.9
Mean	**0.79**	**0.80**	**0.81**	**0.80**	**0.38**	**0.85**
Median	**0.8**	**0.80**	**0.81**	**0.81**	**0.37**	**0.84**

SD	**0.07**	**0.04**	**0.06**	**0.09**	**0.15**	**0.05**
Min	**0.67**	**0.72**	**0.69**	**0.61**	**0.19**	**0.78**
Max	**0.91**	**0.88**	**0.92**	**0.95**	**0.72**	**0.93**
Test of Difference (Mann-Whitney)	**20328*** **	**21068*** **	**20537*** **	**19846*** **	**21508*** **	**19572** **
T-test	**4.6769*** **	**5.7715*** **	**5.7715*** **	**2.5326* **	**5.9312*** **	**3.2629** **

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001; Min, Max and SD mean minimum, maximum and standard deviation respectively.*

As the comprehensive MEA efficiency scores can be decomposed into its variable-specific components, we also computed and reported the disaggregated scores for each insurance type measured relative to the pooled meta-frontier in Table 4.12 (across individual insurers) and Table 4.13 (across time), which allows us to assess not just efficiency levels but also efficiency patterns like other studies (Asmild & Matthews, 2012). Also included in the Tables are the summary statistics of the average efficiencies for each of the two insurance groups.

It is observed that claims efficiency for both life (89%) and non-life (85%) insurers were the highest average variable-specific efficiency. In terms of the leading life insurers that reported the highest disaggregated efficiencies, Met Life (almost 100%) and Enterprise Life (almost 100%) came on top for fixed assets, labour, equity capital, investment income, and claims, whilst SIC Life and Enterprise Life led net premium efficiency on average. On average, the lowest performing life insurer on all variable-specific efficiency scores was CDH Life. In other words, to be as fully efficient as its referent sets, CDH Life would have to reduce the use of fixed assets by 33%, labour by 26%, equity capital by 27%, claims by 24% and augment net premium and investment income by 29% and 79% respectively. Turning attention to non-life insurers, the highest variable-specific efficiencies were obtained by Regency Alliance Insurance (Regency AI) on fixed assets (91%) and equity capital (92%) and Equity Insurance Company (Equity IC), which recorded the highest disaggregated scores on all outputs and labour. On average, non-life insurers that obtained the lowest variable-specific efficiencies on fixed assets, labour and investment income was SIC Insurance Company, on equity capital was Ghana Union Assurance (Ghana UA), on the net premium was Prime Insurance (Prime I) and on claims was Glico Ghana Insurance (Glico GI). Whereas Regency Alliance Insurance was the best non-life insurer in utilising fixed assets and equity capital, Equity Insurance Company was the best on utilizing labour and generating more desirable outputs with less undesirable output. The utilization of fixed assets and labour and the generation of investment income by SIC Insurance Company needs maximum improvement to operate effectively in the insurance market. This finding is in line with Danquah et al. (2018) who observed SIC Insurance Company to be the least DEA cost-efficient insurer despite being the largest non-life insurer in terms of fixed assets. A cursory glance at the middle and the lower part of Table 4.12 depicts the summary statistics which reveals that life insurers are consistently more efficient than non-life insurers across all variable-specific efficiency scores. Once again, we examine the differences between the disaggregated efficiencies of the life and non-life insurers using the traditional nonparametric Wilcoxon-Mann-Whitney test to test whether the average variable-specific efficiencies are statistically different between the two insurance groups. The findings for each disaggregated efficiency led to the conclusion that significant disaggregating efficiency difference exist between life and non-life insurers at the 0.1% level of significance. This was also corroborated with the parametric t-test.

Once again, Figure 4.9 illustrates the violin charts of 12 years pooled average of disaggregated efficiency scores categorized and compared between life and non-life insurers. Though like the box-plot and kernel density plots, the violin plot has added advantages of presenting the evolution of efficiency scores on both central tendencies, spreads and density or distributions, presenting presence of clusters and the densities highlighting the peaks, bumps and valleys in the efficiency distributions (Färe et al., 2015; Hintze & Nelson, 1998; Richter et al., 2021). From the violin plot, a wide spread of all variable-specific efficiency scores (except net

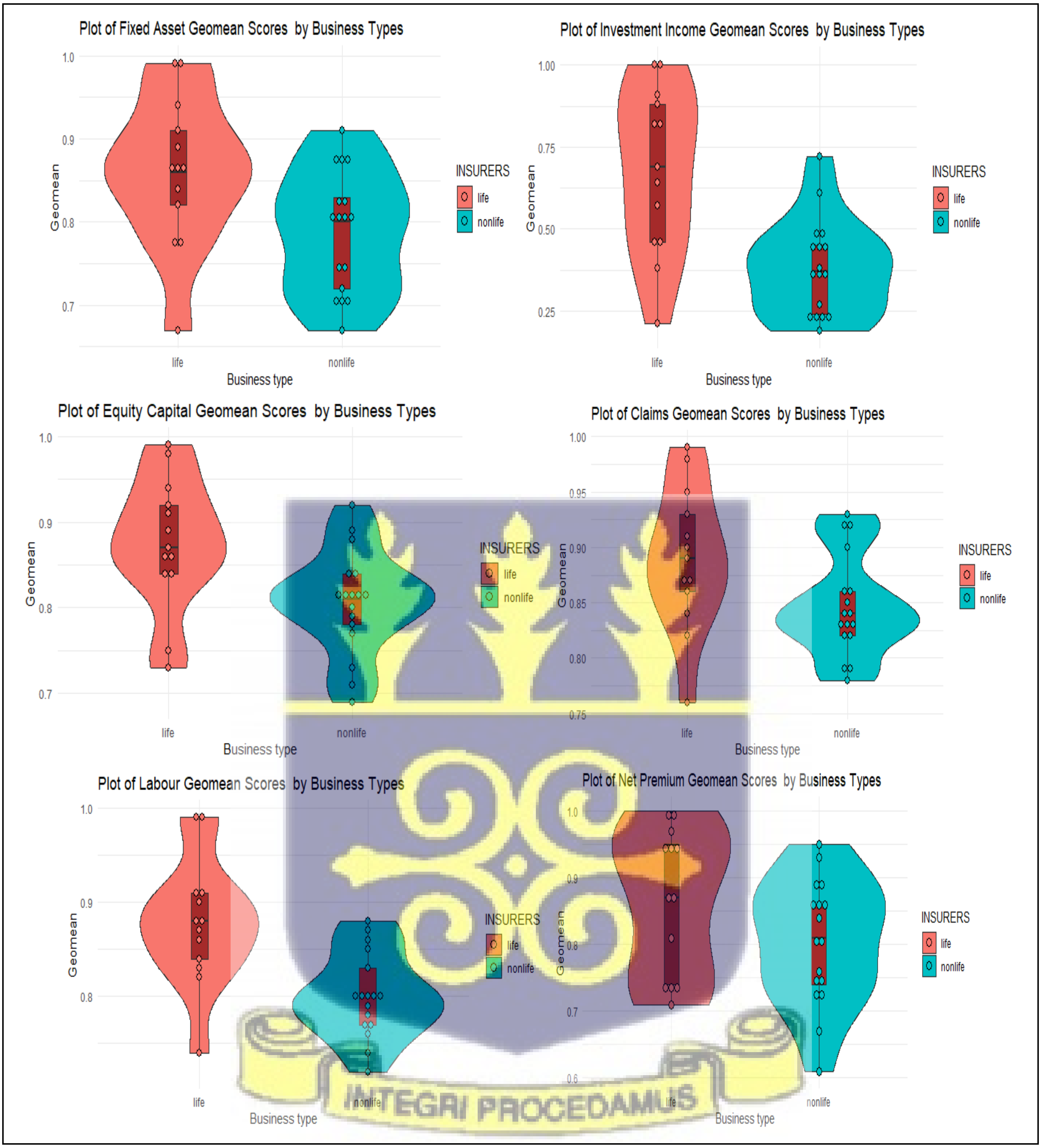


Figure 4.9: Variable-specific efficiency of life and non-life insurers

premium efficiencies) are observed for the life insurers. Non-life insurers, on the other hand, are shown to relatively have a shorter spread for the variables except for investment income efficiencies. These results suggest a wide spread of performance level among the life insurers (0.20, 1) but a relatively shorter spread for the non-life insurers (0.20, 0.95). Relatively fat variable-specific efficiency distributions are observed for the non-life insurers. Except for investment income, the bumps in the variable-specific efficiencies of the non-life insurers are shown to be around lower levels of efficiency signifying lower levels of efficiency scores. However, the bumps of the variable-specific efficiencies of the life insurers are shown around higher efficiency levels. Overall, the life insurers outperformed non-life insurers on all variables.

Table 4.13: Variable-specific efficiencies of life and non-life insurers

		2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
FA	L	0.85	0.83	0.83	0.83	0.85	0.87	0.87	0.91	0.79	0.91	0.87	0.87
	NL	0.84	0.82	0.79	0.72	0.71	0.78	0.77	0.9	0.77	0.81	0.83	0.72
LAB	L	0.87	0.83	0.87	0.86	0.86	0.9	0.88	0.93	0.84	0.91	0.88	0.89
	NL	0.88	0.82	0.8	0.74	0.72	0.79	0.76	0.89	0.82	0.85	0.83	0.73
EC	L	0.86	0.84	0.89	0.86	0.93	0.94	0.84	0.89	0.8	0.92	0.88	0.85
	NL	0.85	0.85	0.83	0.75	0.77	0.83	0.74	0.88	0.77	0.87	0.81	0.72
NP	L	0.78	0.79	0.89	0.81	0.9	0.92	0.85	0.88	0.8	0.9	0.87	0.81
	NL	0.86	0.83	0.81	0.63	0.74	0.87	0.8	0.89	0.88	0.91	0.88	0.65
II	L	0.24	0.29	0.22	0.6	0.85	0.83	0.81	0.9	0.63	0.81	0.76	0.74
	NL	0.16	0.11	0.06	0.18	0.38	0.47	0.63	0.69	0.6	0.72	0.57	0.46
CL	L	0.87	0.84	0.88	0.85	0.91	0.91	0.89	0.94	0.87	0.94	0.92	0.86
	NL	0.88	0.82	0.85	0.76	0.81	0.88	0.85	0.91	0.89	0.9	0.92	0.73

**p-value < 0.05; **p-value < 0.01; ***p-value < 0.001*

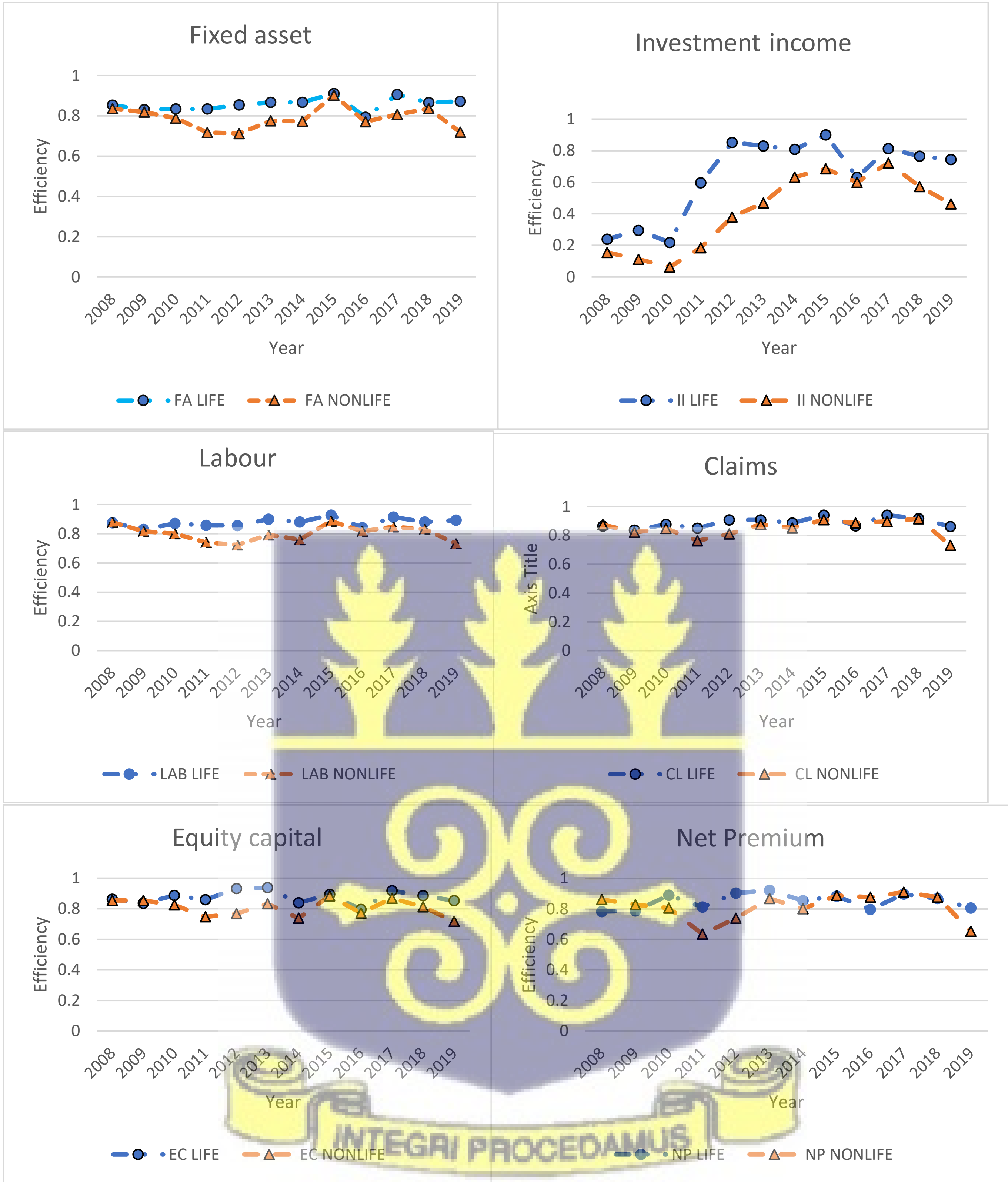


Figure 4.10: Variable-specific efficiencies of life and non-life insurers

A detailed examination of the pooled average variable-specific efficiency differences between life and non-life insurers for each of the input and output variables are shown in Table 4.13 and illustrated in Figure 4.10. Using this information, we can examine not only the levels but the patterns of efficiency differences between life and non-life insurers. From Table 4.13, fixed assets, labour, equity capital, investment income and claims efficiencies of the life insurers are generally found to be more efficient over time than non-life insurers. The average efficiency difference in net premium between life and non-life insurers fluctuated over time.

Figure 4.10 depicts the average efficiency scores for each insurer type in each year for each of the variables measured relative to the meta-frontier with the life insurers being consistently more efficient than the nonlife insurers on investment income, fixed asset, equity capital and labour, with no clear difference between them on claims and net premium during the study period. Based on the patterns, life insurers outperformed non-life insurers on fixed assets, labour, equity capital and investment income.

4.3.5 Insurance efficiency determinants

The sensitivity of non-parametric efficiency models (DEA) to outliers and sampling variations makes it unsuitable to solely depend on efficiency scores to make statistical inferences (Daraio & Simar, 2007). Besides, environmental variations around firms cannot be overlooked, considering their direct impact on firm performance (Dyson et al., 2001). As a results, the assessment of the robustness of non-parametric efficiency scores, second-stage analysis, cannot be ignored during efficiency assessment. This study's fourth objective is to explore the exogenous covariates that affect the efficiency of insurance firms in Ghana.

4.3.5.1 Second stage data description

The descriptive statistics of a dataset gives a detailed statistical description of the dataset sampled for analysis. The quantitative description and distribution of the data gives an insight and broader understanding of the nature and behaviour of the data sampled for the study and upon which conclusions can be made for the study. Based on previous insurance efficiency studies, potential insurance efficiency determinants were selected namely: competition, leverage, size, solvency, profitability, type of insurer and underwriting risk. Table 4.14 depicts the summary statistics of the second stage data sampled for the second stage analysis. The Table shows the variables chosen for the robust econometric models, the number of observations, mean values, standard deviation, minimum and maximum values of each variable chosen for the study.

Table 4.14: Descriptive statistics of second stage analysis data.

Variable	Mean	SD	Min	Max	Count
Eff	0.6146	0.3294	0.0103	1.0000	360
BI	-0.8147	0.4309	-1.6176	-0.2562	360
Lev	1.4893	16.5535	0.0007	314.6018	360
Size	17.3203	1.3830	10.8540	22.7245	360
Solv	2.2859	2.2304	-3.6480	10.8328	360
ROA	0.0759	1.0750	-1.9151	20.1826	360
TOI	0.4333	0.4962	0.0000	1.0000	360
Urisk	0.4387	0.4159	0.0238	6.0938	360

Eff: MEA comprehensive efficiency; BI: Boone Indicator; Lev: Leverage; Solv: Solvency; ROA: Return on Assets; TOI: Type of Insurer; Urisk: Underwriting risk; Min: Minimum; Max: Maximum; SD: Standard deviation.

In testing for multicollinearity among the various second stage variables, the study employed the Pearson’s correlation coefficient matrix and the variance inflation factor (VIF) to check for multicollinearity among the variables chosen for the study. The correlation coefficient index provides the magnitude and directional relationship between two sets of variables without causality implications (Pindyck & Rubinfeld, 1991) and the VIF test analysis is used to determine the viability of multicollinearity of the variables employed for the second-stage analysis. The results from both tests are presented in Table 4.15.

Table 4.15: Correlation matrix of regressors and MEA efficiency scores

Variable	Eff	BI	Lev	Size	Solv	ROA	TOI	Urisk	VIF
Eff	1								
BI	-0.23***	1							1.02
Lev	-0.01	-0.06	1						**43.48**
Size	-0.03	0.02	-0.25***	1					1.1
Solv	0.04	0.11**	-0.06	0.05	1				1.05
ROA	-0.02	-0.07	**0.99*** **	-0.22***	-0.03	1			**42.91**
TOI	0.29***	-0.01	-0.05	0.04	0.02	-0.06	1		1.06
Urisk	-0.08	0.03	-0.01	0.00	0.11**	-0.02	0.22***	1	1.07

***p-value < 0.05; ***p-value < 0.01; Eff: MEA comprehensive efficiency; BI: Boone Indicator; Lev: Leverage; Solv: Solvency; ROA: Return on Assets; TOI: Type of Insurer; Urisk: Underwriting risk.*

Taking precedence from the work of Kennedy (2008), 0.7 is usually set as the threshold to indicate the occurrence of high collinearity among exogenous variables using the Pearson's correlation matrix. However, from the correlation matrix in Table 4.15, there is a strong significant positive relationship (0.99) between leverage and ROA with corresponding VIF of 43.48 and 42.91 respectively. That is to say, an increase in leverage results in a corresponding increase in the ROA of insurers. Hair et al. (1995) posits that a VIF test value above 10 is problematic and an indication of strong multicollinearity among variables however O'Brien (2007) suggests that higher values of VIF do not by themselves discount the results of regression analyses, neither do they call for the elimination of one or more independent variables from the analysis. Hence, none of the second stage variables were eliminated from the study.

4.3.5.2 Results of regression analysis of the whole sample

Aside the two-step systems GMM (an instrumental variable regression), several tests have been undertaken to determine the appropriate and robust static regression model (pooled OLS, FE, RE) for the study. To begin with, the results (p-value = 0.032) of the Chow test for poolability, as specified as in equation 3.16, request the rejection of the null hypothesis, dataset is poolable. This implies that a panel regression model is appropriate for this study. Second, a Durbin-Wu-Hausman (DWH) test, as specified in equation 3.17, was undertaken to determine the appropriate panel regression model (fixed effect (FE) or random effect (RE)) for the study. Its result (p-value = 0.9807) required the study to fail to reject the null hypothesis, the unobserved individual-specific effects are uncorrelated with all the exogenous variables. This meant that, the random effect (RE) model is appropriate for the study.

Next, the results (p-value = 0.00) of the Breusch-Godfrey test for panel data, as specified in equation (3.18), identified the existence of autocorrelation in the study data at a 5% level of significance. As a result, robust standard errors were employed to address the serial correlation/autocorrelation present in the study data. The study further tested for the presence of heteroskedasticity using the Breusch–Pagan LM and the Pesaran's CD (2006) using equations 3.20 and 3.21 respectively. Based on the results provided in Table 4.16, the null hypothesis of constant variance was rejected in favour of the alternative hypothesis of a varying variance as the p-values for both tests were less than the significance level, 5%. In addressing the presence of heteroskedasticity in the study data, robust standard errors were applied to properly estimate the standard errors.

With the results of the preceding tests demonstrating the existence of heteroskedasticity and serial correlation in the study data, the PSCE estimator of Beck and Katz (1995) was used. This estimator and its robust standard errors for the chosen random effect are depicted in

Table 4.16:Total sample regression results

Dependent Variable: Eff Independent Variables	**Pooled OLS** (1)	**Fixed Effect** (2)	**Random Effect** (3)	**RE-HAC** (4)	**RE Beck Katz-PCSE** (5)	**RE Driscoll-SCC** (6)	**Two steps System GMM** (7)	**(8)**	(9)	**Expected signs**
Lag(Eff)							0.125***	**0.3527*** **	0.189***	
							(0.032)	**(0.117)**	(0.041)	
BI	0.183***	0.180***	0.181***	0.181***	0.181***	0.181***	0.109***	**0.473***	0.101***	+
	(0.038)	(0.034)	(0.034)	(0.053)	(0.035)	(0.027)	(0.018)	**(0.206)**	(0.017)	
Lev	0.005	0.005	0.005	0.005	0.005	0.005		**-**	0.000	+
	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.017)		**-**	(0.000)	
Size	-0.01	-0.013	-0.012	-0.12	-0.012	-0.012	-0.007	**-0.025**	-0.001	±
	(0.012)	(0.012)	(-0.012)	(0.009)	(0.013)	(0.013)	(0.008)	**(0.015)**	(0.008)	
Solv	0.013	0.012	0.012	0.012	0.012	0.012	-0.001	**-0.002**	-0.0107	±
	(0.007)	(0.008)	(0.007)	(0.007)	(0.09)	(0.012)	(0.008)	**(0.010)**	(0.009)	
ROA	-0.085	-0.077	-0.079	-0.079	-0.079	-0.079	-0.011	**0.001**	-	+
	(0.098)	(0.095)	(0.094)	(0.120)	(0.130)	(0.218)	(0.061)	**(0.006)**	-	
TOIlife	0.784***	-	-	-	-	-	0.005*	**0.556**	0.003	±
	(0.217)	-	-	-	-	-	(0.002)	**(0.289)**	(0.002)	
TOInon-life	0.574**	-	0.212***	-0.212***	-0.212***	-0.212***		**-**	-	
	(0.215)	-	(0.054)	(0.0480)	(0.063)	(0.049)		**-**	-	
Urisk	-0.126**	-0.135***	-0.132***	-0.132	-0.132*	-0.132	-0.005	**-0.114**	-0.021	±
	(0.04)	(0.04)	(0.039)	(0.091)	(0.053)	(0.181)	(0.027)	**(0.931)**	(0.020)	
Intercept			0.821***	0.821***	0.821***	0.821***		**-**	-	
			(0.211)	(0.167)	(2.0628)	(0.185)		**-**	-	
Diagnostic Tests	**POLS**	**Fixed Effect**	**Random Effect**	**RE-HAC**	**RE-PCSE**	**RE SCC**	**Two steps**			

	(1)	(2)	(3)	(4)	(5)	(6)	**System GMM** (7)			
R-squared	0.168	0.112	0.133							
F-Statistic	193.322***	6.796***	54.093***							
Chow test for poolability	0.032(1.33)									
DWH Test (RE verse FE)			0.9807 (54.109)							
Breusch-Godfrey test for serial correlation			0.00 (46.714)							
Breusch-Pagan test for cross-sectional dependence (RE)			0.00 (730.5)							
Pesaran CD test for cross-sectional dependence (RE)			0.00 (6.984)							
AR(1)							0.0656	**0.1471**	0.4182	
AR(2)							0.0646	**0.1471**	0.4182	
J Hansen							0.0613	**0.9586**	0.138	
Wald test							0.000	**0.00**	0.00	
No. of insurers	30	30	30							
Observations	360	360	360				360	**360**	360	
Number of instruments							43	**47**	49	
AIC							173	**171.7386**	171.8821	
BIC							208.084	**202.8274**	202.971	

Note: Robust Standard errors in parentheses. **p-value < 0.1; **p-value < 0.05; ***p-value < 0.*

Table 4.16 under the column labelled RE Beck & Katz-SCC. Poveda (2011) has criticized this method of correcting heteroskedasticity and serial correlation in data to poorly handling data with large panel cross-sectional dimensions. Hence, the robust standard errors of Driscoll and Kraay (1998) was also applied on the random effect model to account for serial correlation, heteroscedasticity and cross-sectional dependence while relying on the ability of the PSCE estimator to ensure a consistent covariance matrix, independent of the cross-sectional dimension (Poveda, 2011). These results are shown in Table 4.16. Among the three robust random effect models (RE-HAC, RE-PCSE and RE-SCC) used, models (4) and (6) were observed to have two significant variables, whereas model (5) had three significant variables. Hence, model 5 could be selected as the preferred model. The static panel models (pooled OLS, random effects, fixed effects, RE-HAC, PCSE, and SCC) are good in allowing for the control of unobserved heterogeneity thereby ensuring unbiased estimates. However, the static panel models do not make room for endogenous regressors which usually happens in real market systems. As a results, the two-step system GMM is chosen as the preferred model in the study.

In Table 4.16, three regression models, (7) – (9), were estimated with the two-step system GMM measure. First, a generalised model, (7), which uses all the environmental variables of the study. Second, a model which excludes leverage, (8), then one which excludes only ROA, (9). In line with Chowdhury and Zelenyuk (2016), the Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of the three models were estimated to identify the simplest parsimonious model for the study. The elimination of leverage and ROA from model (7) and (8) was due to the strong positive correlation between these two variables (see Table 4.15). Based on the results of the BIC and AIC presented in Table 4.16, model (8) is chosen as the appropriate regression model for the study.

From model (8), the estimated coefficient of the lag of the aggregate efficiency scores has a positive significant impact on aggregate efficiency, signifying that, an insurer's previous year's overall efficiency score positively impacts its current overall performance at 0.1% significance level. This finding is consistent with Sultana & Rahman (2020) which identified a positive relationship between the cost efficiency of banks in Bangladesh and its lag. This means that insurer efficiency in the previous year were also efficient in the current year hence, Ghanaian insurers can improve their present performance by improving their past performance.

The Boone Indicator (BI) which was used to measure the level of competition among insurers, showed a negative significant impact on integrated efficiency scores at 5% significance level. That is, holding all other factors constant, on average, a percentage increase in the level of competition among insurers is associated with 47.3% decrease in the performance of Ghanaian insurers. This finding agrees with the prior expectation of the study and previous insurance efficiency studies (Alhassan & Biekpe, 2016; Barros et al., 2010). This finding also supports the "quiet-life" hypothesis of Hicks (1935) which proposes that competitive insurance markets improve efficiency. This suggests that competition in the Ghanaian insurance sector improves the comprehensive efficiency of Ghanaian insurers.

Leverage, size, solvency, ROA, type of insurer, underwriting risk were all observed to have insignificant impact on the comprehensive efficiency of insurers. This suggests that changes in these exogenous variables do not affect the performance of Ghanaian insurers. These findings contradict Ohene-Asare et al. (2019), Ansah-Adu et al. (2012) and Alhassan et al. (2015) is consistent with Ansah-Adu et al. (2012) on the impact of TOI.

4.4 Chapter summary

This chapter presented the results and discussions of a hypothesised data and the study data. The analysis and discussions of the study data were in line with the objectives of the study.

The first objective of the study sought to mathematically model claims as an undesirable output and to compare the efficiency estimates of claims as a desirable and an undesirable output. This objective was undertaken by evaluating the efficiency scores of the sampled insurers with claims as a desirable and an undesirable output. The results showed that claims efficiency could be underestimated or overestimated depending on whether it was considered as a desirable or undesirable. Furthermore, significant difference was identified between the rankings of the desirable and undesirable claims efficiency estimates at the 0.1% level of significance. With the confirmed difference between the two efficiencies, the claims-specific efficiencies of insurers were analysed, using claims as an undesirable output. The results for this analysis revealed the same median efficiency in 2016 and 2013, even though fatter densities were depicted for the year 2013. Overall, insurers performed well on claims in 2013 and 2015. However, 2019 recorded the worst claim performance of insurers.

The second objective of the study sought to assess the input/output-specific efficiencies of Ghanaian insurers in a disaggregated view. To achieve this objective, the 12-year pooled data for the insurers were pooled and the average comprehensive and the variable-specific efficiency scores for the insurer were examined. In an aggregated view, little improvement is required by insurers to raise desirable output or cut inputs and undesirable outputs. Based on the variable-specific efficiencies, insurers were observed to be performing relatively well on claims and labour. With the exception of investment income, insurers were observed to perform well on the variable-specific efficiencies than on the comprehensive efficiency.

The third objective also sought to assess the comprehensive and variable-specific MEA efficiency differences between life and non-life insurers. Here, the pooled meta-analysis of the comprehensive MEA efficiency scores of the life and non-life insurers across the 2008-2019 periods was used. On average, life insurers were observed to significantly outperform non-life insurers at 0.1% significance level on the comprehensive efficiency. The performance of the insurers varied on the utilisation of inputs and the generation of investment income.

The final objective of the study investigated the exogenous covariates of insurers in Ghana. Using the second stage non-parametric analysis, the MEA integrated insurance efficiencies were regressed on some insurance-specific factors; competition, solvency, size, type of insurer, underwriting risk, leverage and profitability using robust econometric models such as the pooled OLS, FE, RE, RE-HAC, RE-PCSE, RE-SCC and the two-step system GMM model. The results of the two-step system GMM model revealed significant positive impact of competition and the lagged dependent variable on insurance efficiency in Ghana.

CHAPTER FIVE

SUMMARY, CONCLUSION AND RECOMMENDATIONS

5.1 Introduction

The final chapter of this study is made up of three sections. The first section presents the summary, the second uses the key findings to make conclusions and the third section presents recommendations for policy, practice and further academic research.

5.2 Summary of the study

The main purpose of this study was to evaluate the input/output-specific efficiencies of Ghanaian insurers over a sample of 30 insurers from 2008 to 2019, and to pinpoint variable potentials across life and non-life insurers in Ghana. Despite the positive impact of insurance on economic growth and development, there has not been significant growth in insurance penetration rate in Ghana. Despite the plethora of insurance efficiency and dynamic productivity change studies undertaken, very few are focused on Ghana and to the best of the author's knowledge, none has assessed the disaggregated efficiencies of Ghanaian insurers.

The novel MEA model postulated by Bogetoft and Hougaard (1999) and further operationalised by Asmild et al. (2003) was used to assess the aggregated and disaggregated efficiencies of Ghanaian insurers. Specifically, the modified MEA model of Zhu et al. (2019) was used for the non-oriented efficiency assessment under the CRS technology. The inputs; fixed assets, labour, and equity capital, desirable outputs; net premium, investment income and an undesirable output; claims of 13 life and 17 non-life insurers were sampled from the NIC for the periods 2008 - 2019. Just like other insurance efficiency studies, this study investigated the impact of competition, size, solvency, leverage, type of insurer, underwriting risk and profitability on the comprehensive efficiency of Ghanaian insurers using robust econometric models like the pooled OLS, FE, RE, RE-HAC, RE-PSCE, RE-SCC and the two-step system GMM model. The two-step system GMM model was chosen and used to make conclusions and interpretations of the second-stage analysis. The study's key findings are as follows:

i. Given the pooled summary statistics, on average, insurers received GHS28,640,604 as equity capital, injected GHS4,920,182 and GHS14,340,536 into fixed assets and labour costs respectively, generated GHS31,835,053 from net premium and GHS9,223,024 from investment income, and finally spent GHS13,885,505 on claims. With the exception of labour, significant differences were identified in each input and output variable across the 12-year study period.

ii. At the group level, non-life insurers recorded high and insignificant levels of inputs than life insurers even though outputs generated by life businesses were significantly high.

iii. Statistically, the CRS technology was identified as the RTS technology of the Ghanaian insurance sector.

iv. On average, insurers recorded lower efficiency scores when claims were considered as a desirable than an undesirable output. This meant that claims efficiency could be underestimated or overestimated when used as a desirable or undesirable output in insurance efficiency analysis. The rankings of the desirable and undesirable claims estimates were observed to be significantly different at 0.1% level of significance.

v. With claims being considered as an undesirable output, the same median efficiency was obtained in 2016 and 2013. However, fatter densities were illustrated in 2013 than in 2016. Even though a relatively small proportion of insurers operated at full claim efficiency in 2019 and 2011, a greater proportion of insurers attained full claims efficiency in 2015, 2017 and 2018. Overall, the claims performance of insurers was good in 2013 and 2015 but relatively poor in 2019.

vi. On average, insurers recorded 82% comprehensive efficiency. This suggests very little potential for insurers to reduce inputs and undesirable outputs or raise desirable outputs. Based on the variable-specific efficiencies, fat efficiency densities were depicted for claims and labour on high-efficiency scores. However, very low efficiencies were obtained for investment income.

vii. On average, life insurers (mean = 63%) were consistently more efficient than non-life insurers (mean = 44%). Besides, the number of efficient life insurers increased steadily across entire the study period. This means that, the overall performance of life insurers outperformed non-life insurers and based on a Mann-Whitney U test, the difference in performance was confirmed to be at a 0.1% significance level.

viii. In a disaggregated view, efficiency differences were identified between life and the non-life insurers on fixed assets, labour, equity capital and investment income.

ix. The lagged dependent variable and competition were identified to have positive and significant impact on the comprehensive efficiency of Ghanaian insurers. No significant impact was identified for size, solvency, leverage, profitability, type of insurer and underwriting risk. That is to say, the performance of Ghanaian insurers is determined by the previous year's performance and the level of competition in the industry.

5.3 Conclusion

The findings of the study have brought to fore important issues that require ample consideration on insurance efficiency assessment. First, the use of claims as a desirable output does not provide the appropriate claim performance level of insurers. Hence, claims must be used as an undesirable output in insurance efficiency estimation to avoid misleading efficiency scores. Second, the sole use of the comprehensive efficiency of insurers does not provide accurate information on the utilisation and generation of the input and output variables of insurers respectively. Third, Ghanaian life insurers are more efficient than Ghanaian non-life insurers, they outperform non-life insurers on the utilisation of inputs and the generation of investment income. Finally, the level of competition in the insurance industry has the highest impact on the performance of Ghanaian insurers followed by the previous year's performance of insurers. However, size, solvency, type of insurer and underwriting risk do not have a significant impact on the efficiency of Ghanaian insurers.

5.4 Recommendations

A number of recommendations on policy, practice and further academic research can be made from the findings and conclusion made in the preceding sections, The recommendations are as follows:

For policy:

i. The NIC must enact policies to guide the selection and management of investment products in the Ghanaian insurance industry. Much attention should be paid on the amount of investment income reported by insurers in their quarterly reports, this will help the NIC identify potential downfalls with investment income generation. Furthermore, the NIC could organise investment training sessions for insurers. Insurers must also be obligated to invest with well-performing financial institutions.

For practice:

i. Insurance managers must improve their performance on investment income. They should be crucial in the selection and management of their investment products.

ii. Non-life insurance managers must improve their overall performance. They must also learn from life insurance managers on how to utilise inputs and generate more investment income.

For academic research:

i. Further research should be undertaken to assess the input/output-specific dynamic productivity change and cost efficiency of Ghanaian insurers in the presence of undesirable outputs with the novel MEA model.

ii. Future studies should assess the efficiency contribution of insurer variables on comprehensive efficiency to identify the specific contribution(s) of the variables on insurer comprehensive efficiency.

iii. Future studies should also explore the determinants of the variable-specific efficiencies.

5.6 Limitations of the study

Despite the law guiding the submission of audited annual reports to the NIC, the audited annual reports of some insurers were not obtained from the NIC. Hence, 16 figures had to be mathematically generated (linearly interpolation) in R.

5.7 Chapter summary

This chapter presented a detailed summary of the study. The study concludes that life insurers outperform non-life insurers and identifies competition to have a positive and significant impact on insurer performance in Ghana. Future studies could assess the input/output-specific dynamic productivity change and cost efficiency of Ghanaian insurers in the presence of undesirable outputs with the novel MEA model.

References

Akhtar, M. H (2013). After the financial crisis: a cost efficiency analysis of banks from Saudi Arabia. *International Journal of Islamic and Middle Eastern Finance and Management*, *6*(4), 322–332. https://doi.org/10.1108/IMEFM-05-2013-0059

Agbloyor, E. K., Gyeke-Dako, A., Kuipo, R., & Abor, J. Y. (2016). Foreign direct investment and economic growth in SSA: The role of institutions. *Thunderbird International Business Review*, 58(5), 479-497.

Al-Amri, K., Gattoufi, S., & Al-Muharrami, S. (2012). Analyzing the technical efficiency of insurance companies in GCC. *The Journal of Risk Finance*.

Al-Amri, K. (2015). Takaful insurance efficiency in the GCC countries. *Humanomics*, *31*(3), 344–353. https://doi.org/10.1108/H-05-2014-0039

Al-Amri, K., Gattoufi, S., & Al-Muharrami, S. (2012). Analyzing the technical efficiency of insurance companies in GCC. *Journal of Risk Finance*, *13*(4), 362–380. https://doi.org/10.1108/15265941211254471

Alhassan, A. L., Addisson, G. K., & Asamoah, M. E. (2015). Market structure, efficiency and profitability of insurance companies in Ghana. *International Journal of Emerging Markets*, *10*(4), 648–669. https://doi.org/10.1108/IJoEM-06-2014-0173

Alhassan, A. L., & Biekpe, N. (2015). Efficiency, productivity and returns to scale economies in the non-life insurance market in South Africa. *Geneva Papers on Risk and Insurance: Issues and Practice*, *40*(3), 493–515. https://doi.org/10.1057/gpp.2014.37

Alhassan, A. L., & Biekpe, N. (2016). Competition and efficiency in the non-life insurance market in South Africa. *Journal of Economic Studies*, *43*(6), 882–909. https://doi.org/10.1108/JES-07-2015-0128

Alhassan, A. L., & Biekpe, N. (2018). Competition and Risk-Taking Behaviour in the Non-

Life Insurance Market in South Africa. *The Geneva Papers on Risk and Insurance - Issues and Practice*, *43*(3), 492–519. https://doi.org/10.1057/s41288-017-0074-z

Alhassan, A. L., & Ohene-Asare, K. (2016). Competition and bank efficiency in emerging markets: empirical evidence from Ghana. *African Journal of Economic and Management Studies*, *7*(2), 268–288. https://doi.org/10.1108/AJEMS-01-2014-0007

Allen, R., & Thanassoulis, E. (2004). Improving envelopment in data envelopment analysis. *European Journal of Operational Research*, *154*(2), 363–379. https://doi.org/10.1016/S0377-2217(03)00175-9

Amirteimoori, A., Kordrostami, S., & Sarparast, M. (2006). Modeling undesirable factors in data envelopment analysis. *Applied Mathematics and Computation*, *180*(2), 444–452. https://doi.org/10.1016/j.amc.2005.12.029

Ansah-Adu, K., Andoh, C., & Abor, J. (2012). Evaluating the cost efficiency of insurance companies in Ghana. *Journal of Risk Finance*, *13*(1), 61–76. https://doi.org/10.1108/15265941211191949

Apergis, N., Aye, G. C., Barros, C. P., Gupta, R., & Wanke, P. (2015). Energy efficiency of selected OECD countries: A slacks based model with undesirable outputs. *Energy Economics*, *51*, 45–53. https://doi.org/10.1016/j.eneco.2015.05.022

Arabi, B., Munisamy, S., & Emrouznejad, A. (2015). A new slacks-based measure of Malmquist-Luenberger index in the presence of undesirable outputs. *Omega (United Kingdom)*, *51*, 29–37. https://doi.org/10.1016/j.omega.2014.08.006

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The review of economic studies, 58(2), 277-297.

Asare, N., Alhassan, A. L., Asamoah, M. E., & Ntow-Gyamfi, M. (2017). Intellectual capital and profitability in an emerging insurance market. *Journal of Economic and Administrative Sciences*, *33*(1), 2–19. https://doi.org/10.1108/jeas-06-2016-0016

Asmild, M., Balezentis, T., & Hougaard, J. L. (2016). Multi-directional productivity change: MEA-Malmquist. *Journal of Productivity Analysis*, *46*(2–3), 109–119. https://doi.org/10.1007/s11123-016-0486-y

Asmild, M., Baležentis, T., & Hougaard, J. L. (2016). Multi-directional program efficiency: the case of Lithuanian family farms. *Journal of Productivity Analysis*, *45*(1), 23–33. https://doi.org/10.1007/s11123-014-0419-6

Asmild, M., Hougaard, J. L., Kronborg, D., & Kvist, H. K. (2003). Measuring Inefficiency via Potential Improvements. *Journal of Productivity Analysis*, *19*(1), 59–76. https://doi.org/10.1023/A:1021822103696

Asmild, M., Kronborg, D., Mahbub, T., & Matthews, K. (2019). The efficiency patterns of Islamic banks during the global financial crisis: The case of Bangladesh. *Quarterly Review of Economics and Finance*, *74*, 67–74. https://doi.org/10.1016/j.qref.2018.04.004

Asmild, M., Kronborg, D., & Matthews, K. (2016). Introducing and modeling inefficiency contributions. *European Journal of Operational Research*, *248*(2), 725–730. https://doi.org/10.1016/j.ejor.2015.07.060

Asmild, M., & Matthews, K. (2012). Multi-directional efficiency analysis of efficiency patterns in Chinese banks 1997-2008. *European Journal of Operational Research*, *219*(2), 434–441. https://doi.org/10.1016/j.ejor.2012.01.001

Asmild, M., & Pastor, J. T. (2010). Slack free MEA and RDM with comprehensive efficiency measures. *Omega*, *38*(6), 475–483. https://doi.org/10.1016/j.omega.2009.12.004

Assaf, G. A., Matousek, R., & Tsionas, E. G. (2013). Turkish bank efficiency: Bayesian estimation with undesirable outputs. *Journal of Banking and Finance*, *37*(2), 506–517.

https://doi.org/10.1016/j.jbankfin.2012.09.009

Atkinson, S. E., & Dorfman, J. H. (2005). Bayesian measurement of productivity and efficiency in the presence of undesirable outputs: Crediting electric utilities for reducing air pollution. *Journal of Econometrics*, *126*(2), 445–468. https://doi.org/10.1016/j.jeconom.2004.05.009

Avkiran, N. K. (1999). An application reference for data envelopment analysis in branch banking: helping the novice researcher. *International Journal of Bank Marketing*, *17*(5), 206–220. https://doi.org/10.1108/02652329910292675

Baležentis, T., & De Witte, K. (2015). One- and multi-directional conditional efficiency measurement - Efficiency in Lithuanian family farms. *European Journal of Operational Research*, *245*(2), 612–622. https://doi.org/10.1016/j.ejor.2015.01.050

Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, *30*(9), 1078–1092. https://doi.org/10.1287/mnsc.30.9.1078

Banker R.D. (1996). Hypothesis Tests Using Data Envelopment Analysis. *Journal of Productivity Analysis*, *7*, 139–159. http://www.ingentaconnect.com/content/klu/prod/1996/00000007/F0020002/00117395

Barros, C. P., & Dieke, P. U. C. (2008). Measuring the economic efficiency of airports: A Simar-Wilson methodology analysis. *Transportation Research Part E: Logistics and Transportation Review*, *44*(6), 1039–1051. https://doi.org/10.1016/j.tre.2008.01.001

Barros, C. P., Nektarios, M., & Assaf, A. (2010). Efficiency in the Greek insurance industry. *European Journal of Operational Research*, *205*(2), 431–436. https://doi.org/10.1016/j.ejor.2010.01.011

Barros, C. P., & Wanke, P. (2014). Insurance companies in Mozambique: A two-stage DEA and neural networks on efficiency and capacity slacks. *Applied Economics*, *46*(29), 3591–3600. https://doi.org/10.1080/00036846.2014.934436

Beck, N., & Katz, J. N. (1995). With not to do (and not to do) with Time-Series Cross-Section Data. *The American Political Science Review*, *89*(3), 634–647.

Beck, T., De Jonghe, O., & Schepens, G. (2013). Bank competition and stability: Cross-country heterogeneity. *Journal of Financial Intermediation*, *22*(2), 218–244. https://doi.org/10.1016/j.jfi.2012.07.001

Bell, A., & Jones, K. (2015). Explaining fixed effects: Random effects modeling of time-series cross-sectional and panel data. *Political Science Research and Methods*, 3(1), 133-153.

Berger, A.N., Brockett, P. L., Cooper, W. W., & Pastor, J. T. (1997). New approaches for analyzing and evaluating the performance of financial institutions. *European Journal of Operational Research*, *98*(2), 170–174. https://doi.org/10.1016/s0377-2217(96)00341-4

Berger, A. N, & Humphrey, D. B. (1992). Measurement and efficiency issues in commercial banking. In *Output Measurement in the Service Sectors* (Issue January). http://ideas.repec.org/h/nbr/nberch/7237.html

Bhargava, A., Jamison, D. T., Lau, L. J., & Murray, C. J. (2001). Modeling the effects of health on economic growth. *Journal of health economics*, 20(3), 423-440.

Bhattacharyya, A. (2012). Adjustment of inputs and measurement of technical efficiency: A dynamic panel data analysis of the Egyptian manufacturing sectors. *Empirical economics*, 42(3), 863-880.

Bi, G., Wang, P., Yang, F., & Liang, L. (2014). Energy and environmental efficiency of china's transportation sector: A Multidirectional analysis approach. *Mathematical Problems in Engineering*, *2014*, 539596. https://doi.org/10.1155/2014/539596

Biener, C., & Eling, M. (2012). Organization and efficiency in the international insurance industry: A cross-frontier analysis. *European Journal of Operational Research*, *221*(2), 454–468. https://doi.org/10.1016/j.ejor.2012.03.037

Biener, C., Eling, M., & Wirfs, J. H. (2016). The determinants of efficiency and productivity in the Swiss insurance industry. *European Journal of Operational Research*, *248*(2), 703–714. https://doi.org/10.1016/j.ejor.2015.07.055

Bikker, J. A., & van Leuvensteijn, M. (2008). Competition and efficiency in the Dutch life insurance industry. *Applied Economics*, *40*(16), 2063–2084. https://doi.org/10.1080/00036840600949298

Blanche, M. T., Blanche, M. J. T., Durrheim, K., & Painter, D. (2006). *Research in practice: Applied methods for the social sciences*. Juta and Company Ltd.

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of econometrics*, 87(1), 115-143.

Bogetoft, P., & Hougaard, J. L. (1999). Efficiency Evaluations Based on Potential (Non-Proportional) Improvements. *Journal of Productivity Analysis*, *12*(3), 233–247. https://doi.org/10.1023/A:1007848222681

Boone, J. (2001). Intensity of competition and the incentive to innovate. *International Journal of Industrial Organization*, *19*(5), 705–726. https://doi.org/10.1016/S0167-7187(00)00090-4

Boone, J. (2008). A new way to measure competition. *The Economic Journal*, *118*, *118*(2002), 1245–1261.

Boone, J., Griffith, R., & Harrison, R. (2005). Measuring competition. *AIM Re.*

Breusch, T. ., & Pagan, A. . (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica*: *Journal of the econometric society*, 1287–1294. https://www.jstor.org/stable/1911963

Breusch, T. S., & Godfrey, L. G. (1981). A review of recent work on testing for autocorrelation in dynamic simultaneous models. In *Macroeconomic Analysis, Essays in Macroeconomics and Economics* (Vol. 1).

Breusch, T. S., & Pagan, A. R. (1980). The lagrange multiplier test and its applications to model specification in econometrics. *The Review of Economic Studies*, *47*(1), 239. https://doi.org/10.2307/2297111

Brooks, C. (2008). *Introductory Econometrics for Finance*.

Chakrabarti, A., & Shankar, A. (2015). Determinants of health insurance penetration in india: an empirical analysis. *Oxford Development Studies*, *43*(3), 379–401. https://doi.org/10.1080/13600818.2015.1057116

Charnes, A., Copper, W. ., & Rhodes, E. (1978). Measuring the efficiency of decision making units. *European journal of operational research*, 2(6), 429–444.

Chen, B., Powers, M. R., & Qiu, J. (2009). Life-insurance efficiency in China: A comparison of foreign and domestic firms. *China and World Economy*, *17*(6), 43–63. https://doi.org/10.1111/j.1749-124X.2009.01173.x

Chen, L., Wang, Y. M., & Lai, F. (2017). Semi-disposability of undesirable outputs in data envelopment analysis for environmental assessments. *European Journal of Operational Research*, *260*(2), 655–664. https://doi.org/10.1016/j.ejor.2016.12.042

Chen, M. S., & Lai, G. C. (2010). Distribution systems, loyalty and performance. *International Journal of Retail and Distribution Management*, *38*(9), 698–718. https://doi.org/10.1108/09590551011062448

Chowdhury, H., & Zelenyuk, V. (2016). Performance of hospital services in Ontario: DEA with truncated regression approach. *Omega (United Kingdom)*, *63*, 111–122. https://doi.org/10.1016/j.omega.2015.10.007

Clark, E., Radić, N., & Sharipova, A. (2018). Bank competition and stability in the CIS markets. *Journal of International Financial Markets, Institutions and Money*, *54*(2018), 190–203. https://doi.org/10.1016/j.intfin.2017.12.005

Coelli, T., Rao, D. S. P., O'Donnell, C. J. ., & Battese, G. E. (2005). *An Introduction to Eefficiency and Productivity Analysis*.

Cook, W. D., & Zhu, J. (2005). *Data envelopment analysis. Modeling Performance Measurement.*

Cooper, W., Seiford, L., & Zhu, J. (2004). *Handbook on Data Envelopment Analysis - International Series in Operations Research & Management Science*.

Cooper, W. W., Seiford, L. M., & Zhu, J. (2011). Data envelopment analysis: History, models, and interpretations. In *International Series in Operations Research and Management Science* (Vol. 164). https://doi.org/10.1007/978-1-4419-6151-8_1

Creswell, J. W., & Creswell, J. D. (2018). Creswell, John W. Creswell, J. David. In *SAGE Publication,Inc* (Issue 2).

Cummins, D. J., & Rubio-Misas, M. (2006). Deregulation , consolidation , and efficiency : evidence from the Spanish insurance industry. *Journal of Money, Credit, and Banking*, *38*(2), 323–355.

Cummins, D. J., Rubio-Misas, M., & Vencappa, D. (2017). Competition, efficiency and soundness in European life insurance markets. *Journal of Financial Stability*, *28*, 66–78. https://doi.org/10.1016/j.jfs.2016.11.007

Cummins, D. J., Rubio-Misas, M., & Zi, H. (2004). The effect of organizational structure on efficiency: Evidence from the Spanish insurance industry. *Journal of Banking and Finance*, *28*(12), 3113–3150. https://doi.org/10.1016/j.jbankfin.2004.05.004

Cummins, D. J., & Weiss, M. A. (1993). Measuring cost efficiency in the property-liability insurance industry. *Journal of Banking and Finance*, *17*(2–3), 463–481. https://doi.org/10.1016/0378-4266(93)90046-G

Cummins, D. J., & Weiss, M. A. (2013). Analyzing Firm Performance in the Insurance Industry Using Frontier Efficiency and Productivity Methods. In *Handbook of Insurance: Second Edition*. https://doi.org/10.1007/978-1-4614-0155-1

Cummins, D. J., Weiss, M. A., Xie, X., & Zi, H. (2010). Economies of scope in financial services: A DEA efficiency analysis of the US insurance industry. *Journal of Banking and Finance*, *34*(7), 1525–1539. https://doi.org/10.1016/j.jbankfin.2010.02.025

Cummins, D., Tennyson, S., & Weiss, M. A. (1999). Consolidation and efficiency in the US life insurance industry. *Journal of Banking and Finance*, *23*(2), 325–357. https://doi.org/10.1016/S0378-4266(98)00089-2

Cummins, J. D., & Xie, X. (2013). Efficiency, productivity, and scale economies in the U.S. property-liability insurance industry. *Journal of Productivity Analysis*, *39*(2), 141–164. https://doi.org/10.1007/s11123-012-0302-2

Danquah, M., Otoo, D. M., & Baah-Nuakoh, A. (2018). Cost efficiency of insurance firms in Ghana. *Managerial and Decision Economics*, *39*(2), 213–225. https://doi.org/10.1002/mde.2897

Daraio, C., Kerstens, K., Nepomuceno, T., & Sickles, R. C. (2020). Empirical surveys of frontier applications: a meta-review. *International Transactions in Operational Research*, *27*(2), 709–738. https://doi.org/10.1111/itor.12649

Daraio, C., & Simar, L. (2007). *Advanced robust and nonparametric methods in efficiency analysis, methodology and applications*.

Debreu, G. (1951). The coefficient of resource utilization. *Journal of the Econometric Society*, *19*(3), 273–292. http://www.jstor.com/stable/1906814

Demsetz, H. (1973). Industry structure , market rivalry , and public policy. *The Journal of Law and Economics*, *16*(1), 1–9.

Diacon, S. R., Starkey, K., & O'Brien, C. (2002). Size and efficiency in european long-term insurance companies: an international comparison. *Geneva Papers on Risk and Insurance: Issues and Practice*, *27*(3), 444–466. https://doi.org/10.1111/1468-0440.00184

Driscoll, J. C., & Kraay, A. C. (1998). Consistent covariance matrix estimation with spatially dependent panel data. *Review of Economics and Statistics*, *80*(4), 549–559. https://doi.org/10.1162/003465398557825

Durbin, J. (1954). Error in variables. *Review of the International Statistical Institute, 22:* 23–32.

Dyckhoff, H., & Allen, K. (2001). Measuring ecological efficiency with data envelopment analysis (DEA). *European Journal of Operational Research*, *132*(2), 312–325. https://doi.org/10.1016/S0377-2217(00)00154-5

Dyckhoff, H. (2018). Financial and sustainability performance evaluation. *Journal of Business Economics*, *88*(7), 851–882. https://doi.org/10.1007/s11573-017-0885-1

Dyson, R. G., Allen, R., Camanho, A. S., Podinovski, V. V., Sarrico, C. S., & Shale, E. A. (2001). Pitfalls and protocols in DEA. *European Journal of Operational Research*, *132*(2), 245–259. https://doi.org/10.1016/S0377-2217(00)00149-1

Eling, M., & Jia, R. (2018). Business failure, efficiency, and volatility: Evidence from the European insurance industry. *International Review of Financial Analysis*, *59*(July), 58–76. https://doi.org/10.1016/j.irfa.2018.07.007

Eling, M., & Luhnen, M. (2010). Efficiency in the international insurance industry: A cross-country comparison. *Journal of Banking and Finance*, *34*(7), 1497–1509.

https://doi.org/10.1016/j.jbankfin.2009.08.026

Eling, M., & Schaper, P. (2017). Under pressure: how the business environment affects productivity and efficiency of European life insurance companies. *European Journal of Operational Research*, *258*(3), 1082–1094. https://doi.org/10.1016/j.ejor.2016.08.070

Emrouznejad, A., Parker, B. R., & Tavares, G. (2008). Evaluation of research in efficiency and productivity: A survey and analysis of the first 30 years of scholarly literature in DEA. *Socio-Economic Planning Sciences*, *42*(3), 151–157. https://doi.org/10.1016/j.seps.2007.07.002

Emrouznejad, A., & Yang, G. liang. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. *Socio-Economic Planning Sciences*, *61*, 4–8. https://doi.org/10.1016/j.seps.2017.01.008

Fare, R., & Grosskopf, S. (1985). A nonparametric cost approach to scale efficiency. *The Scandinavian Journal of Economics*. *87*(4), 594–604.

Färe, R., & Grosskopf, S. (2004). Modeling undesirable factors in efficiency evaluation: Comment. *European Journal of Operational Research*, *157*(1), 242–245. https://doi.org/10.1016/S0377-2217(03)00191-7

Färe, R., Grosskopf, S., Maudos, J., & Tortosa-ausina, E. (2015). Revisiting the quiet life hypothesis in banking using nonparametric techniques. *Journal of Business Economics and Management*, *16*(1), 159–187. https://doi.org/10.3846/16111699.2012.726929

Färe, R., Grosskopf, S., Noh, D. W., & Weber, W. (2005). Characteristics of a polluting technology: Theory and practice. *Journal of Econometrics*, *126*(2), 469–492. https://doi.org/10.1016/j.jeconom.2004.05.010

Farrell, M. J. (1957). The Measurement of Productive Efficiency. *Journal of the Royal Statistical Society: Series A (General)*, *120*(3), 253–290. http://goo.gl/AFhm2N

Fernández, C., Koop, G., & Steel, M. F. J. (2002). Multiple-output production with undesirable outputs: An application to nitrogen surplus in agriculture. *Journal of the American Statistical Association*, *97*(458), 432–442. https://doi.org/10.1198/016214502760046989

Firebaugh, G., Warner, C., & Massoglia, M. (2013). Fixed effects, random effects, and hybrid models for causal analysis. *In Handbook of Causal Analysis for Social Research* (pp. 113-132). Springer, Dordrecht.

Fox, J. (2000). Decision theory : Bayesian. *International Encyclopedia of Social & Behavioral Sciences*.

Fried, H. O., Lovell, C. A. K., & Schmidt, S. S. (Eds.). (2008). *The Measurement of Productive Efficiency and Productivity Growth*. Oxford University Press, Inc.

Frisch, R. (1964). *Theory of Production.* Springer Science & Business Media.

Gaganis, C., Hasan, I., & Pasiouras, F. (2013). Efficiency and stock returns: Evidence from the insurance industry. *Journal of Productivity Analysis*, *40*(3), 429–442. https://doi.org/10.1007/s11123-013-0347-x

Gardner, L. A., & Grace, M. F. (1993). X-Efficiency in the US life insurance industry. *Journal of Banking and Finance*, *17*(2–3), 497–510. https://doi.org/10.1016/0378-4266(93)90048-I

Giantsios, D. G., & Noulas, A. G. (2020). Cost efficiency and convergence in the european nonlife insurance industry. *Journal of Applied Finance & Banking*, *10*(6), 1792–6599.

Golany, B., & Yaakov, R. (1989). An application procedure of DEA. *Omega*, *17*(3), 237–250.

Greene, W. H., & Segal, D. (2004). Profitability and efficiency in the U.S. life insurance industry. *Journal of Productivity Analysis*, *21*(3), 229–247. https://doi.org/10.1023/B:PROD.0000022092.70204.fa

Guba, C. E. (1990). The Paradigm Dialog

Gunasekara, F. I., Richardson, K., Carter, K., & Blakely, T. (2014). Fixed effects analysis of repeated measures data. *International Journal of Epidemiology*, 43(1), 264-269.

Han, L., Li, D., Moshirian, F., & Tian, Y. (2010). Insurance development and economic growth. *Geneva Papers on Risk and Insurance: Issues and Practice*, *35*(2), 183–199. https://doi.org/10.1057/gpp.2010.4

Hancock, D. (1985). The financial firm: production with monetary and nonmonetary goods. *Journal of Political Economy*, *93*(5), 859–880. https://doi.org/10.1086/261339

Hancock, G. R., Mueller, R. O., & Stapleton, L. M. (2010). *The reviewer's guide to quantitative methods in the social sciences*. Routledge.

Hansson, S. O. (1991). An overview of case-based decision theory. *Uncertain Decisions*, *January*, 215–235. https://doi.org/10.1007/978-1-4615-5083-9_10

Hansson, S. O. (2005). *A Brief Introduction* (Issue January 2005).

Hauk, W. R., & Wacziarg, R. (2009). A Monte Carlo study of growth regressions. *Journal of Economic Growth*, 14(2), 103-147.

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, 1251–1271.

Hicks, J. R. (1935). Annual survey of economic theory : the theory of monopoly. *Econometrica: Journal of the Econometric Society*, 1–20.

Hintze, J. L., & Nelson, R. D. (1998). Violin plots: A box plot-density trace synergism. *American Statistician*, *52*(2), 181–184. https://doi.org/10.1080/00031305.1998.10480559

Ho, S. J., & Hsu, H. H. (2021). The effect of microinsurance on the insurance market: evidence from Taiwan. *Geneva Papers on Risk and Insurance: Issues and Practice*, *46*(1), 130–

145. https://doi.org/10.1057/s41288-020-00175-6

Holvad, T., Hougaard, J. L., Kronborg, D., & Kvist, H. K. (2004). Measuring inefficiency in the Norwegian bus industry using multi-directional efficiency analysis. *Transportation*, *31*(3), 349–369. https://doi.org/10.1023/B:PORT.0000025400.33939.6d

Huang, T. H., Liu, N. H., & Kumbhakar, S. C. (2018). Joint estimation of the Lerner index and cost efficiency using copula methods. *Empirical Economics*, *54*(2), 799–822. https://doi.org/10.1007/s00181-016-1216-z

Huang, W., & Eling, M. (2013). An efficiency comparison of the non-life insurance industry in the BRIC countries. *European Journal of Operational Research*, *226*(3), 577–591. https://doi.org/10.1016/j.ejor.2012.11.008

Ibrahim, M., & Alagidede, P. (2017). Financial sector development, economic volatility and shocks in sub-Saharan Africa. *Physica A: Statistical Mechanics and Its Applications*, *484*, 66–81. https://doi.org/10.1016/j.physa.2017.04.142

Kader, H. A., Adams, M., Hardwick, P., & Kwon, W. J. (2014). Cost efficiency and board composition under different takaful insurance business models. *International Review of Financial Analysis*, *32*, 60–70. https://doi.org/10.1016/j.irfa.2013.12.008

Kaffash, S., Azizi, R., Huang, Y., & Zhu, J. (2020). A survey of data envelopment analysis applications in the insurance industry 1993–2018. *European Journal of Operational Research*, *284*(3), 801–813. https://doi.org/10.1016/j.ejor.2019.07.034

Kapelko, M., & Lansink, A. O. (2017). Dynamic multi-directional inefficiency analysis of European dairy manufacturing firms. *European Journal of Operational Research*, *257*(1), 338–344. https://doi.org/10.1016/j.ejor.2016.08.009

Kasman, A., & Turgutlu, E. (2009). Cost efficiency and scale economies in the Turkish insurance industry. *Applied Economics*, *41*(24), 3151–3159.

https://doi.org/10.1080/00036840701367663

Kennedy, P. (2008). *A Guide to Econometrics. A Guide to Econometrics (Vol. 6)*. Oxford: Blackwell Publishing Ltd. Retrieved from http://books. google. com/books.

Khan, S. A. M. N., Ramli, R., & Baten, A. (2018). A slack based enhanced DEA model with undesirable outputs for rice growing farmers efficiency measurement. *International Journal of Supply Chain Management*, *7*(1), 194–200.

Koopmans, T. C. (1951). Efficient Allocation of Resources. *Econometrica: Journal of the Econometric Society*, *19*(4), 455–465.

Kouki, I., & Al-Nasser, A. (2017). The implication of banking competition: Evidence from African countries. *Research in International Business and Finance*, *39*, 878–895. https://doi.org/10.1016/j.ribaf.2014.09.009

Kumbhakar, S. C., Ortega-Argilés, R., Potters, L., Vivarelli, M., & Voigt, P. (2012). Corporate R&D and firm efficiency: Evidence from Europe's top R&D investors. *Journal of Productivity Analysis*, *37*(2), 125–140. https://doi.org/10.1007/s11123-011-0223-5

Labajova, K., Hansson, H., Asmild, M., Göransson, L., Lagerkvist, C. J., & Neil, M. (2016). Multidirectional analysis of technical efficiency for pig production systems: The case of Sweden. *Livestock Science*, *187*, 168–180. https://doi.org/10.1016/j.livsci.2016.03.009

Laeven, L., & Levine, R. (2009). Bank governance, regulation and risk taking. *Journal of Financial Economics*, *93*(2), 259–275. https://doi.org/10.1016/j.jfineco.2008.09.003

Lampe, H. W., & Hilgers, D. (2015). Trajectories of efficiency measurement: A bibliometric analysis of DEA and SFA. *European Journal of Operational Research*, *240*(1), 1–21. https://doi.org/10.1016/j.ejor.2014.04.041

Lee, C. C., Chiu, Y. Bin, & Chang, C. H. (2013). Insurance demand and country risks: A nonlinear panel data analysis. *Journal of International Money and Finance*, *36*, 68–85.

https://doi.org/10.1016/j.jimonfin.2013.03.009

Lerner, A. P. (1934). The concept of monopoly and the measurement of monopoly power. *Review of Economic Studies*, *1*(3), 157–175. https://doi.org/10.2307/2967480

Levine, R., Loayza, N., & Beck, T. (2000). Financial intermediation and growth: Causality and causes without outliers. *Journal of Monetary Economics*, *46*(1), 31–77. https://doi.org/10.1007/s10258-009-0035-y

Lim, Q.-M., Lee, H. S., & Har, W.-M. (2020). Efficiency, productivity and competitiveness of the Malaysian insurance sector: an analysis of risk-based capital regulation. *Geneva Papers on Risk and Insurance: Issues and Practice*, *46*(1), 146–172. https://doi.org/10.1057/s41288-020-00173-8

Liu, J., Gong, Y., Zhu, J., & Titah, R. (2021). Information technology and performance: Integrating data envelopment analysis and configurational approach. *Journal of the Operational Research Society*, *0*(0), 1–16. https://doi.org/10.1080/01605682.2021.1907238

Liu, J. S., Lu, L. Y. Y., Lu, W. M., & Lin, B. J. Y. (2013a). A survey of DEA applications. *Omega (United Kingdom)*, *41*(5), 893–902. https://doi.org/10.1016/j.omega.2012.11.004

Liu, J. S., Lu, L. Y. Y., Lu, W. M., & Lin, B. J. Y. (2013b). Data envelopment analysis 1978-2010: A citation-based literature survey. *Omega (United Kingdom)*, *41*(1), 3–15. https://doi.org/10.1016/j.omega.2010.12.006

Lovell, C. A. K. (1993). Productive efficiency. *The Measurement of Productive Efficiency: Techniques and Applications*, 3–67. https://doi.org/10.4324/9780203749159-3

Lozano, S. (2016). Slacks-based inefficiency approach for general networks with bad outputs: An application to the banking sector. *Omega (United Kingdom)*, *60*, 73–84. https://doi.org/10.1016/j.omega.2015.02.012

Lozano, S., & Soltani, N. (2020). Efficiency assessment using a multidirectional DDF approach. *International Transactions in Operational Research*, *27*(4), 2064–2080. https://doi.org/10.1111/itor.12617

Luhnen, M. (2009). Determinants of efficiency and productivity in german property-liability insurance: Evidence for 1995-2006. *Geneva Papers on Risk and Insurance: Issues and Practice*, *34*(3), 483–505. https://doi.org/10.1057/gpp.2009.10

Maghbouli, M., Amirteimoori, A., & Kordrostami, S. (2014). Two-stage network structures with undesirable outputs: A DEA based approach. *Measurement: Journal of the International Measurement Confederation*, *48*(1), 109–118. https://doi.org/10.1016/j.measurement.2013.10.032

Mahlberg, B., & Url, T. (2010). Single Market effects on productivity in the German insurance industry. *Journal of Banking and Finance*, *34*(7), 1540–1548. https://doi.org/10.1016/j.jbankfin.2009.09.005

Manevska-Tasevska, G., Hansson, H., Asmild, M., & Surry, Y. (2018). *Assessing the regional efficiency of Swedish agriculture under the CAP – a multidirectional efficiency approach*.

Manevska-Tasevska, G., Hansson, H., Asmild, M., & Surry, Y. (2021). Exploring the regional efficiency of the Swedish agricultural sector during the CAP reforms – multi-directional efficiency analysis approach. *Land Use Policy*, *100*(October 2019), 104897. https://doi.org/10.1016/j.landusepol.2020.104897

Mavi, N. K., & Mavi, R. K. (2019). Energy and environmental efficiency of OECD countries in the context of the circular economy: Common weight analysis for malmquist productivity index. *Journal of Environmental Management*, *247*(June), 651–661. https://doi.org/10.1016/j.jenvman.2019.06.069

McDonald, J. (2009). Using least squares and tobit in second stage DEA efficiency analyses.

European Journal of Operational Research, *197*(2), 792–798. https://doi.org/10.1016/j.ejor.2008.07.039

Mendoza, M., & Gutleierrex-Pena, E. (2017). Decision theory. *The Cambridge History of Moral Philosophy*, 706–717. https://doi.org/10.1017/9781139519267.054

Miles, M. B., & Huberman, A. M. (1994). *Qualitative data analysis: An expanded sourcebook*. sage.

Molinos-Senante, M., Gémar, G., Gómez, T., Caballero, R., & Sala-Garrido, R. (2016). Eco-efficiency assessment of wastewater treatment plants using a weighted Russell directional distance model. *Journal of Cleaner Production*, *137*, 1066–1075. https://doi.org/10.1016/j.jclepro.2016.07.057

Morgan, D. L. (2007). Paradigms Lost and Pragmatism Regained: Methodological Implications of Combining Qualitative and Quantitative Methods. *Journal of Mixed Methods Research*, *1*(1), 48–76. https://doi.org/10.1177/2345678906292462

Newey, W. K., & West, K. D. (1987). Hypothesis testing with efficient method of moments Estimation. *International Economic Review*, 777–787.

NIC. (2010). *National Insurance Commission Annual Report*.

NIC. (2012). *National Insurance Commission Annual Report*.

NIC. (2017). *National Insurance Commission Annual Report*.

NIC. (2018). *National Insurance Commission Annual Report*.

NIC. (2019). *National Insurance Commission Annual Report*.

Nickel, S. 1981. Biases in Dynamic Models with Fixed Effects. *Econometrica* 49(6): 1417– 26

Nourani, M., Chandran, V., Kweh, Q. L., & Lu, W. M. (2018). Measuring Human, Physical and Structural Capital Efficiency Performance of Insurance Companies. *Social Indicators*

Research, *137*(1), 281–315. https://doi.org/10.1007/s11205-017-1584-6

Ohene-Asare, K., Asare, J. K. A., & Turkson, C. (2019). Dynamic cost productivity and economies of scale of Ghanaian insurers. *Geneva Papers on Risk and Insurance: Issues and Practice*, *44*(1), 148–177. https://doi.org/10.1057/s41288-018-0111-6

Ohene-Asare, K., & Asmild, M. (2012). Banking efficiency analysis under corporate social responsibilities. *International Journal of Banking, Accounting and Finance*, *4*(2), 146–171. https://doi.org/10.1504/IJBAAF.2012.048331

Ohene-Asare, K., Turkson, C., & Afful-Dadzie, A. (2017). Multinational operation, ownership and efficiency differences in the international oil industry. *Energy Economics*, *68*, 303–312. https://doi.org/10.1016/j.eneco.2017.10.006

Oppong, G. K., Pattanayak, J. K., & Irfan, M. (2019). Impact of intellectual capital on productivity of insurance companies in Ghana: A panel data analysis with System GMM estimation. *Journal of Intellectual Capital*, *20*(6), 763–783. https://doi.org/10.1108/JIC-12-2018-0220

Owusu-Ansah, E., Dontwi, I., Seidu, B., Abudulai, G., & Sebil, C. (2010). Technical efficiencies of Ghanaian general insurers. *American Journal of Social and Management Sciences*, *1*(1), 75–87. https://doi.org/10.5251/ajsms.2010.1.1.75.87

Pesaran, H. (2006). Estimation and Inference in Large Heterogeneous Panels with a Multifactor Error Structure. *Econometrica*, *74*(4), 967–1012. http://www.jstor.org/stable/3805914

Pindyck, R. S., & Rubinfeld, D. L. (1991). *Econometric models and economic forecasts*. Irwin, McGraw-Hill.

Plümper, T., & Troeger, V. E. (2007). Efficient estimation of time-invariant and rarely changing variables in finite sample panel analyses with unit fixed effects. *Political analysis*, 15(2), 124-139.

Poveda, A. (2011). Socio-economic development and violence: An empirical application for seven metropolitan areas in Colombia. *Peace Economics, Peace Science and Public Policy*, *17*(1). https://doi.org/10.2202/1554-8597.1223

Pradhan, R. P., Arvin, M. B., Nair, M., Bennett, S. E., & Hall, J. H. (2018). The dynamics between energy consumption patterns, financial sector development and economic growth in Financial Action Task Force (FATF) countries. *Energy*, *159*, 42–53. https://doi.org/10.1016/j.energy.2018.06.094

Rai, A. (1996). Cost efficiency of international insurance firms. *Journal of Financial Services Research*, *10*(3), 213–233. https://doi.org/10.1007/BF00114085

Ramalho, E., Ramalho, J., & Henriques, P. (2010). Towards an idea-centered, principle-base design to as creation approach support learning knowledge. *Educational Technology Research and Development*, *34*(3), 239–255. https://doi.org/10.1007/sl

Reyna, A. M., & Fuentes, H. J. (2018). A cost efficiency analysis of the insurance industry in Mexico. *Journal of Productivity Analysis*, *49*(1), 49–64. https://doi.org/10.1007/s11123-017-0521-7

Richter, A., Ng, K. T. W., Karimi, N., & Chang, W. (2021). Developing a novel proximity analysis approach for assessment of waste management cost efficiency in low population density regions. *Sustainable Cities and Society*, *65*(November 2020), 102583. https://doi.org/10.1016/j.scs.2020.102583

Roberts, F. (1990). Relative Scores. *Journal of Mathematical Analysis and Applications*, 30–52.

Schaeck, B. K., & Cihák, M. (2010). Competition , efficiency , and soundness in banking : An industrial organization perspective. *European banking center discussion paper*, (2010-20S).

Schaeck, K., & Cihak, M. (2014). Competition , efficiency , and stability in banking. *Financial Management*, 43(1). 215–241.

Schmidt, P. (1986). Frontier Production Functions. *Econometrics Reviews*, *2*(June 2013), 289–328. https://doi.org/10.1111/b.9780631216339.1999.00004.x

Seiford, L. M., & Zhu, J. (2002). Modeling undesirable factors in efficiency evaluation. *European Journal of Operational Research*, *142*(1), 16–20. https://doi.org/10.1016/S0377-2217(01)00293-4

Seiford, L., & Thrall, R. (1990). Recent developments in FDR. *The Mathematical Programming Approach to Frontier Analysis Lawrence*, *46*, 7–38. https://doi.org/10.1007/978-3-642-31424-7_52

Shephard, R. W., & Fare, R. (1944). The law of diminishing returns. *Science*, *99*(2571), 267–271. https://doi.org/10.1126/science.99.2571.267

Shephard, R. W. (1970). Theory of cost and production functions. *The Economic Journal*, *82*(327), 1059–1061.

Siddiqui, S. A. (2021). The effect of branch office locations on technical efficiency: evidence from the indian life insurance industry. *Global Business Review*. https://doi.org/10.1177/09721509211027427

Simar, L, & Wilson, P. W. (2002). Non-parametric tests of returns to scale. *European Journal of Operational Research*, 139(1), 115–132.

Simar, L, & Wilson, P. W. (1998). Sensitivity analysis of efficiency scores : How to bootstrap in nonparametric frontier models. *Management science*, 44(1), 49–61.

Simar, L, & Wilson, P. W. (2000). A general methodology for bootstrapping in non-parametric frontier models. *Journal of Applied Statistics*, *27*(6), 779–802. https://doi.org/10.1080/02664760050081951

Simar, L, & Wilson, P. W. (2007). Estimation and inference in two-stage, semi-parametric models of production processes. *Journal of Econometrics*, *136*(1), 31–64. https://doi.org/10.1016/j.jeconom.2005.07.009

Simar, L, & Wilson, P. W. (2011). Inference by the m out of n bootstrap in nonparametric frontier models. *Journal of Productivity Analysis*, *36*(1), 33–53. https://doi.org/10.1007/sl

Stimson, J. A. (1985). Regression in space and time: A statistical essay. *American Journal of Political Science,* 914-947.

Sueyoshi, T., & Goto, M. (2010). Measurement of a linkage among environmental, operational, and financial performance in Japanese manufacturing firms: A use of Data Envelopment Analysis with strong complementary slackness condition. *European Journal of Operational Research*, *207*(3), 1742–1753. https://doi.org/10.1016/j.ejor.2010.07.024

Sultana, I., & Rahman, M. M. (2020). Determinants of bank profitability: empirical evidence from bangladesh. *International Journal of Business and Management*, *10*(8), 39–71. https://doi.org/10.5539/ijbm.v10n8p135

Tan, Y., & Floros, C. (2018). Risk, competition and efficiency in banking: Evidence from China. *Global Finance Journal*, *35*(December), 223–236. https://doi.org/10.1016/j.gfj.2017.12.001

Tone, K. (2001). Slacks-Based measure of efficiency. *International Series in Operations Research and Management Science, 164,* 195–209. https://doi.org/10.1007/978-1-4419-6151-8_8

Tortosa-Ausina, E., Armero, C., Conesa, D., & Grifell-Tatjé, E. (2012). Bootstrapping profit change: An application to Spanish banks. *Computers and Operations Research*, *39*(8), 1857–1871. https://doi.org/10.1016/j.cor.2010.04.017

Tziogkidis, P., Philippas, D., Leontitsis, A., & Sickles, R. C. (2020). A data envelopment analysis and local partial least squares approach for identifying the optimal innovation policy direction. *European Journal of Operational Research*, *285*(3), 1011–1024. https://doi.org/10.1016/j.ejor.2020.02.023

Tziogkidis, P., Philippas, D., & Tsionas, M. G. (2020). Multidirectional conditional convergence in European banking. *Journal of Economic Behavior and Organization*, *173*, 88–106. https://doi.org/10.1016/j.jebo.2020.03.013

van Leuvensteijn, M., Bikker, J. A., van Rixtel, A. A. R. J. M., & Sørensen, C. K. (2011). A new approach to measuring competition in the loan markets of the euro area. *Applied Economics*, *43*(23), 3155–3167. https://doi.org/10.1080/00036840903493234

Wang, K., Yu, S., Li, M. J., & Wei, Y. M. (2015). Multi-directional efficiency analysis-based regional industrial environmental performance evaluation of China. *Natural Hazards*, *75*(2), 273–299. https://doi.org/10.1007/s11069-014-1097-4

Wanke, P., Barros, C. P., & Faria, J. R. (2015). Financial distress drivers in Brazilian banks: A dynamic slacks approach. *European Journal of Operational Research*, *240*(1), 258–268. https://doi.org/10.1016/j.ejor.2014.06.044

Ward, D., & Zurbruegg, R. (2000). Does insurance promote economic growth? Evidence from OECD countries. *Journal of Risk and Insurance*, 489–506.

Wise, W. (2017). A survey of life insurance efficiency papers: Methods, pros & cons, trends. *Accounting*, *3*, 137–170. https://doi.org/10.5267/j.ac.2016.12.001

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. MIT press. *Cambridge, MA*, *108(2), 245-254.*

Wooldridge, M. (2009). *An introduction to multiagent systems.* John wiley & sons.

Wu, D. M. (1973). Alternative tests of independence between stochastic regressors and disturbances. *Econometrica: journal of the Econometric Society*, *733-750.*

Wu, D., Yang, Z., Vela, S., & Liang, L. (2007). Simultaneous analysis of production and investment performance of Canadian life and health insurance companies using data envelopment analysis. *Computers and Operations Research*, *34*(1), 180–198. https://doi.org/10.1016/j.cor.2005.05.005

Xu, Y. (2017). Generalized synthetic control method: Causal inference with interactive fixed effects models. *Political Analysis*, 25(1), 57-76.

Yang, Z. (2006). A two-stage DEA model to evaluate the overall performance of Canadian life and health insurance companies. *Mathematical and Computer Modelling*, *43*(7–8), 910–919. https://doi.org/10.1016/j.mcm.2005.12.011

Yao, S., Han, Z., & Feng, G. (2007). On technical efficiency of China's insurance industry after WTO accession. *China Economic Review*, *18*(1), 66–86. https://doi.org/10.1016/j.chieco.2006.10.005

You, S., & Yan, H. (2011). A new approach in modelling undesirable output in DEA model. *Journal of the Operational Research Society*, *62*(12), 2146–2156. https://doi.org/10.1057/jors.2011.1

Yuengert, A. M. (1993). The measurement of efficiency in life insurance: Estimates of a mixed normal-gamma error model. *Journal of Banking and Finance*, *17*(2–3), 483–496. https://doi.org/10.1016/0378-4266(93)90047-H

Zhang, G., & Lin, B. (2018). Impact of structure on unified efficiency for Chinese service sector—A two-stage analysis. *Applied Energy*, *231*(September), 876–886. https://doi.org/10.1016/j.apenergy.2018.09.033

Zhu, J. (2003). *Quantitative models for performance evaluation: data envelopment analysis with operations research & management science*. https://doi.org/10.1007/978-1-4757-4246-6

Zhu, L., Wang, Y., Shang, P., Qi, L., Yang, G., & Wang, Y. (2019). Improvement path, the improvement potential and the dynamic evolution of regional energy efficiency in China: Based on an improved nonradial multidirectional efficiency analysis. *Energy Policy*, *133*(July 2019), 110883. https://doi.org/10.1016/j.enpol.2019.110883

APPENDICES

Appendix A

Tabular taxonomy of multi-directional efficiency analysis studies

No	Author (Year)	Efficiency/ Productivity Measure	Models	Orientation (Input/Output/None)	Inputs	Outputs	Sample, Country, Period	Sector	Findings
1	Asmild et al. 2003	production efficiency	DEA AND MEA	input oriented	• Building costs • Equipment cost, • Capital costs, labour cost, miscellaneous	• gross return	1808 Danish farms (1994)	Agriculture	On average an inefficient farm can save 231726 DKK by reducing inputs to the levels of the selected benchmark
2	Labajova, et al. (2016)	Technical efficiency	MEA	non-orientation	• feed costs • labour • other variable inputs • fixed inputs • landex	• income from pig production & not related to pig production.	71 questionnaires out of 138, Sweden, (2009 – 2011)	Pig production	Advisory services and farm location were not significantly correlated with technical efficiency as well as housing practice.
3	Zhu et al. (2020)	Total factor productivity	MEA MIP & DEA, Meta-frontier framework	non-orientation	• Interest expenses • non-interest expenses	• interest income • non-interest income • non-performing loans	16 main Chinese commercial banks (2005–2015)	Banking	The large state-owned commercial banks performed better than the small medium commercial banks in terms of total factor productivity growth.

4	Asmild & Matthews (2012)	Technical efficiency	MEA	non-orientation	• number of employees • fixed assets • total deposits • non-performing loans.	• net interest • non-interest earnings	14 Chinese banks (1997 – 2008)	Banking	JSBs are more efficient than the SOBs and the SOBs are less efficient than JSBs on utilisation of labour & production of non-performing loans.
5	Kapelko & Lansink (2017)	Dynamic program & managerial inefficiency	MEA	input and investment specific	• labour cost • material cost • investment • fixed assets	• Total revenue	446 large European dairy manufacturing (2005-2012)	Meat processing	Regardless the dynamic inefficiency dimension considered, investments are the most inefficient input, followed by labour, and materials.
6	Asmild, Balezentis & Hougaard (2016)	Managerial efficiency & program efficiency	MEA & DEA	input specific	• value of land • labour cost • intermediate consumption • depreciation	• Total agricultural output	3,308 Lithuanian family farms (2004-2011)	Agriculture	Important differences in variable-specific performance of the farms can be hidden when using the DEA-based Malmquist index.
7	Asmild, Holvad, Hougard & Kronborg. (2009)	Technical efficiency	MEA	input oriented	• staff costs • material purchases • external charges • network length.	• Passenger train • Freight train	23 European countries (1995 – 2001)	Transport	All the reform initiatives have negative impacts on the inefficiencies on both material and staff costs,

8	Bi et al. (2014)	energy & environmental efficiency	MEA	non-orientation	• Labour • fixed capital • investment • volume of energy consumed	• value-added amount • CO_2	30 Chinese provinces in mainland (2006–2010)	Energy, environment & Transport	Identify the energy saving potential and CO_2 emissions reduction potential for each province and area in China in this study
9	Adamie & Hansson (2021)	rational inefficiency	MEA & DEA, Markov transitional dynamic	non-oriented & input-oriented	• variable cost • asset • labour • land	• milk meat outputs • other outputs in farm production	specialist Swedish dairy farms, (2009 – 2016)	Agriculture	The findings show the importance of time dynamics in efficiency achievements with implications to cross-sectional view.
10	Asmild, Kronborg, Mahbub & Matthews (2019)	managerial efficiency	MEA	non-oriented	• personal expenses (labour costs) • non-personal expenses (other cost)	• off-balance earnings • balance-sheet earnings	30 Bangladesh banks (2001–2015)	Banking	Found significantly higher efficiencies of both the inputs (non-labour costs and labour costs) as well as one of the outputs in the time window of the GFC period for the Islamic banks compared to the private conventional banks.

Appendix B

Claims efficiency when desirable

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019
Activa I	1.00	0.48	0.46	0.66	0.66	0.19	0.57	0.41	0.27	0.20	0.18	0.16
CDH L	0.88	0.46	0.99	0.62	0.23	0.16	0.33	0.52	0.53	0.43	0.91	0.86
Donewell IC	0.41	1.00	0.45	0.54	0.89	0.24	0.38	0.29	0.57	0.49	0.45	0.31
Donewell L	1.00	0.90	0.71	0.76	1.00	1.00	1.00	1.00	0.67	0.37	0.49	0.52
Enter L	1.00	1.00	0.78	0.62	1.00	1.00	1.00	1.00	1.00	0.84	1.00	0.49
Enterprise IC	0.63	1.00	0.63	1.00	0.75	0.59	1.00	0.87	1.00	1.00	0.73	0.59
Equity IC	0.59	0.19	0.26	0.44	0.43	0.36	0.49	0.48	0.62	0.31	0.43	0.44
Ghana L	1.00	0.72	0.81	0.76	0.83	0.41	0.63	0.59	0.60	0.17	1.00	1.00
Ghana UA	0.99	0.78	1.00	0.65	0.56	0.53	0.64	0.69	0.58	0.28	0.38	0.66
GhanaUnion L	0.34	0.45	0.42	0.32	0.69	0.86	0.76	0.50	0.53	0.21	0.25	0.42
Glico GI	0.84	0.54	0.57	0.64	0.62	0.34	0.54	0.80	0.83	0.54	0.41	0.30
Glico L	0.72	0.80	0.79	0.76	0.94	0.95	1.00	1.00	0.89	0.73	0.72	1.00
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Metropolitan IC	1.00	0.93	0.92	0.77	0.80	0.85	0.77	0.70	0.74	0.39	1.00	1.00
NSIA GC	0.52	0.70	0.98	0.40	0.45	0.29	0.56	0.24	0.16	0.18	0.16	0.16
Phoenix IC	0.66	0.41	0.54	0.71	0.60	0.61	0.53	0.66	0.56	0.34	0.62	0.73
Phoenix L	1.00	0.07	0.72	0.88	0.97	0.79	1.00	0.95	1.00	1.00	1.00	1.00
Prime I	0.18	0.23	0.96	0.75	0.21	0.02	0.37	0.49	0.55	0.25	0.49	0.45
Provident IC	0.37	0.38	0.43	0.72	0.59	0.25	0.23	0.14	0.24	0.26	0.15	0.28
Provident L	1.00	1.00	0.74	1.00	0.90	1.00	0.96	0.72	0.80	0.57	0.91	1.00
Quality IC	0.74	0.45	0.76	0.65	0.65	0.24	0.36	0.50	0.40	0.23	0.32	0.23
Quality L	0.55	0.38	0.54	0.79	0.95	0.54	1.00	0.92	0.90	1.00	0.65	0.57
Regency AI	0.13	1.00	0.33	0.66	0.59	0.35	0.43	0.75	0.88	0.58	1.00	0.71
SIC IC	0.47	0.41	0.42	0.42	0.55	0.26	0.54	0.61	0.34	0.25	0.24	0.05
SIC L	0.80	0.64	0.81	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Star AC	1.00	0.57	1.00	0.55	0.54	0.50	0.49	0.52	0.66	0.48	0.35	0.69
Star L	1.00	1.00	0.90	1.00	1.00	0.67	0.90	1.00	1.00	0.98	1.00	1.00
Unique IC	1.00	0.31	0.46	0.60	1.00	0.36	0.54	0.54	0.63	0.43	0.36	0.33
Vanguard AC	0.98	1.00	1.00	0.83	0.78	0.62	1.00	0.87	0.84	0.47	0.66	0.78
Vanguard L	1.00	1.00	1.00	1.00	1.00	0.96	0.86	1.00	0.84	0.16	1.00	1.00

Appendix C
Comprehensive efficiency

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.86	0.01	0.03	0.28	0.25	1.00	0.63	0.63	0.63	0.54	0.75	0.40	**0.31**
CDH L	0.01	0.03	0.03	0.31	1.00	0.86	0.72	0.42	0.16	0.26	0.24	0.28	**0.19**
Donewell IC	0.02	0.40	0.23	0.30	0.33	0.51	1.00	1.00	0.63	0.61	0.56	0.36	**0.37**
Donewell L	1.00	0.22	0.09	0.53	1.00	1.00	1.00	1.00	0.44	0.55	0.45	0.25	**0.51**
Enter L	0.70	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.89	**0.96**
Enterprise IC	0.05	1.00	0.02	1.00	0.29	0.47	0.58	1.00	1.00	1.00	0.56	0.45	**0.41**
Equity IC	0.05	1.00	1.00	0.34	1.00	0.62	1.00	1.00	0.60	1.00	0.70	0.56	**0.61**
Ghana L	1.00	0.16	0.13	0.26	0.38	0.56	1.00	0.46	0.51	1.00	1.00	1.00	**0.50**
Ghana UA	0.09	0.33	1.00	0.29	0.52	0.28	0.62	0.80	0.35	0.42	0.27	0.11	**0.35**
GhanaUnion L	0.21	0.65	1.00	0.87	0.89	1.00	0.71	1.00	0.60	1.00	0.65	1.00	**0.75**
Glico GI	1.00	0.22	0.06	0.27	0.31	0.48	0.36	0.41	0.26	0.37	0.46	0.36	**0.32**
Glico L	0.12	0.36	0.11	0.57	0.81	0.50	0.68	1.00	0.37	0.51	0.43	0.44	**0.41**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.63	**0.96**
Metropolitan IC	1.00	0.22	0.17	0.35	0.43	0.63	0.42	0.48	0.44	0.64	0.60	1.00	**0.47**
NSIA GC	0.08	0.15	0.10	0.59	0.68	0.38	0.36	1.00	1.00	1.00	0.83	0.42	**0.41**
Phoenix IC	0.05	0.21	0.11	0.26	0.31	0.62	0.59	0.77	0.58	0.89	0.65	0.56	**0.36**
Phoenix L	1.00	1.00	0.06	0.36	0.61	0.72	0.44	0.74	1.00	1.00	1.00	1.00	**0.62**
Prime I	1.00	0.06	0.01	0.04	0.34	1.00	0.18	1.00	1.00	0.85	0.49	0.36	**0.28**
Provident IC	0.42	0.03	0.03	0.09	0.18	0.30	0.68	0.72	0.67	0.62	1.00	0.55	**0.28**
Provident L	0.42	1.00	1.00	1.00	0.78	1.00	0.37	0.57	0.45	0.66	0.82	1.00	**0.71**
Quality IC	0.05	0.10	0.13	0.38	0.30	0.41	0.58	0.26	0.52	0.69	0.61	0.42	**0.29**
Quality L	0.07	0.22	0.48	0.68	0.53	0.64	1.00	1.00	0.75	1.00	0.72	0.52	**0.53**
Regency AI	1.00	1.00	0.19	0.23	0.40	1.00	1.00	0.72	0.48	0.77	1.00	0.69	**0.62**
SIC IC	0.02	0.03	0.02	0.11	0.32	0.36	0.40	0.42	1.00	0.54	0.32	0.34	**0.19**
SIC L	0.09	0.18	0.84	0.64	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.67**
Star AC	1.00	0.22	1.00	0.45	0.74	0.55	0.70	0.86	0.57	1.00	0.89	0.50	**0.66**
Star L	0.69	0.29	0.29	0.60	0.78	0.75	0.52	1.00	1.00	1.00	1.00	1.00	**0.69**
Unique IC	1.00	0.11	0.03	0.11	1.00	0.54	0.73	1.00	0.52	0.75	1.00	0.60	**0.42**
Vanguard AC	1.00	1.00	1.00	0.33	0.39	0.63	0.67	0.86	0.53	0.70	0.39	0.21	**0.58**
Vanguard L	1.00	1.00	1.00	1.00	0.79	0.64	0.61	1.00	0.38	1.00	1.00	1.00	**0.84**
Geomean	**0.26**	**0.25**	**0.17**	**0.37**	**0.54**	**0.64**	**0.64**	**0.76**	**0.59**	**0.74**	**0.66**	**0.52**	

Appendix D

Pooled variable-specific efficiencies when claims are undesirable

Fixed asset

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.96	0.76	0.75	0.81	0.67	1.00	0.85	0.88	0.73	0.66	0.87	0.71	**0.80**
CDH L	0.70	0.67	0.64	0.62	1.00	0.73	0.71	0.61	0.56	0.63	0.63	0.60	**0.67**
Donewell IC	0.75	0.82	0.76	0.63	0.57	0.67	1.00	1.00	0.72	0.70	0.76	0.62	**0.74**
Donewell L	1.00	0.82	0.75	0.92	1.00	1.00	1.00	1.00	0.59	0.69	0.64	0.66	**0.82**
Enter L	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.90	**0.99**
Enterprise IC	0.70	1.00	0.67	1.00	0.73	0.64	0.92	1.00	1.00	1.00	0.78	0.67	**0.83**
Equity IC	0.67	1.00	1.00	0.64	1.00	0.81	1.00	1.00	0.87	1.00	0.93	0.71	**0.87**
Ghana L	1.00	0.67	0.66	0.62	0.58	0.75	1.00	0.66	0.62	1.00	1.00	1.00	**0.78**
Ghana UA	0.70	0.84	1.00	0.71	0.67	0.64	0.77	0.95	0.55	0.66	0.69	0.52	**0.71**
GhanaUnion L	0.75	0.89	1.00	0.99	1.00	1.00	0.80	1.00	0.80	1.00	0.81	1.00	**0.91**
Glico GI	1.00	0.78	0.72	0.73	0.63	0.72	0.60	0.77	0.57	0.68	0.73	0.66	**0.71**
Glico L	0.81	0.84	0.77	0.87	0.96	0.82	0.95	1.00	0.77	0.82	0.76	0.73	**0.84**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.92	**0.99**
Metropolitan IC	1.00	0.86	0.82	0.87	0.76	0.88	0.68	0.75	0.68	0.77	0.74	1.00	**0.81**
NSIA GC	0.75	0.80	0.77	0.83	0.86	0.64	0.59	1.00	1.00	1.00	0.89	0.63	**0.80**
Phoenix IC	0.76	0.84	0.79	0.77	0.68	0.85	0.78	0.93	0.71	0.88	0.99	0.77	**0.81**
Phoenix L	1.00	1.00	0.71	0.72	0.76	0.86	0.81	0.90	1.00	1.00	1.00	1.00	**0.89**
Prime I	1.00	0.73	0.65	0.60	0.52	1.00	0.54	1.00	1.00	0.90	0.71	0.65	**0.75**
Provident IC	0.66	0.66	0.71	0.61	0.57	0.63	0.67	0.92	0.69	0.70	1.00	0.99	**0.72**
Provident L	0.83	1.00	1.00	1.00	0.81	1.00	0.68	0.82	0.67	0.77	0.85	1.00	**0.86**
Quality IC	0.73	0.71	0.73	0.61	0.70	0.73	0.70	0.63	0.70	0.73	0.78	0.64	**0.70**
Quality L	0.64	0.65	0.78	0.81	0.63	0.69	1.00	1.00	0.76	1.00	0.72	0.70	**0.77**
Regency AI	1.00	1.00	0.88	0.77	0.70	1.00	1.00	0.98	0.83	0.89	1.00	0.91	**0.91**
SIC IC	0.72	0.66	0.71	0.62	0.60	0.65	0.61	0.72	1.00	0.70	0.68	0.50	**0.67**
SIC L	0.61	0.57	0.82	0.68	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.87**
Star AC	1.00	0.84	1.00	0.79	0.93	0.85	0.85	0.96	0.73	1.00	0.92	0.80	**0.88**
Star L	0.97	0.87	0.85	0.79	0.63	0.75	0.61	1.00	1.00	1.00	1.00	1.00	**0.86**
Unique IC	1.00	0.74	0.61	0.61	1.00	0.77	0.85	1.00	0.73	0.78	1.00	0.86	**0.82**
Vanguard AC	1.00	1.00	1.00	0.72	0.73	0.87	0.97	1.00	0.82	0.84	0.85	0.82	**0.88**
Vanguard L	1.00	1.00	1.00	1.00	0.94	0.80	0.86	1.00	0.76	1.00	1.00	1.00	**0.94**
Geomean	**0.84**	**0.82**	**0.81**	**0.77**	**0.77**	**0.81**	**0.81**	**0.91**	**0.78**	**0.85**	**0.85**	**0.78**	

Labour

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.97	0.73	0.72	0.79	0.63	1.00	0.81	0.74	0.82	0.77	0.86	0.73	**0.8**
CDH L	0.75	0.69	0.69	0.68	1.00	0.97	0.83	0.70	0.65	0.67	0.63	0.70	**0.7**
Donewell IC	0.83	0.84	0.84	0.69	0.63	0.75	1.00	1.00	0.89	0.81	0.75	0.67	**0.8**
Donewell L	1.00	0.79	0.73	0.89	1.00	1.00	1.00	1.00	0.72	0.71	0.69	0.70	**0.8**
Enter L	0.98	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.93	**1.0**
Enterprise IC	0.77	1.00	0.74	1.00	0.79	0.78	0.80	1.00	1.00	1.00	0.77	0.73	**0.9**
Equity IC	0.70	1.00	1.00	0.67	1.00	0.83	1.00	1.00	0.83	1.00	0.84	0.76	**0.9**
Ghana L	1.00	0.71	0.74	0.68	0.64	0.79	1.00	0.75	0.73	1.00	1.00	1.00	**0.8**
Ghana UA	0.76	0.84	1.00	0.76	0.71	0.75	0.86	0.92	0.80	0.79	0.68	0.56	**0.8**
GhanaUnion L	0.82	0.90	1.00	0.83	0.82	1.00	0.73	1.00	0.77	1.00	0.77	1.00	**0.9**
Glico GI	1.00	0.80	0.78	0.78	0.65	0.80	0.60	0.78	0.70	0.69	0.72	0.68	**0.7**
Glico L	0.87	0.91	0.84	0.87	0.95	0.85	0.90	1.00	0.90	0.86	0.72	0.75	**0.9**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.87	**1.0**
Metropolitan IC	1.00	0.83	0.77	0.81	0.67	0.85	0.71	0.77	0.71	0.76	0.78	1.00	**0.8**
NSIA GC	0.85	0.77	0.72	0.78	0.84	0.65	0.62	1.00	1.00	1.00	0.88	0.66	**0.8**
Phoenix IC	0.83	0.83	0.84	0.79	0.67	0.76	0.70	0.87	0.73	0.89	0.99	0.75	**0.8**
Phoenix L	1.00	1.00	0.72	0.70	0.69	0.79	0.76	0.87	1.00	1.00	1.00	1.00	**0.9**
Prime I	1.00	0.73	0.68	0.64	0.55	1.00	0.54	1.00	1.00	0.85	0.76	0.69	**0.8**
Provident IC	0.77	0.68	0.65	0.67	0.63	0.69	0.73	0.92	0.84	0.79	1.00	0.99	**0.8**
Provident L	0.93	1.00	1.00	1.00	0.85	1.00	0.76	0.82	0.69	0.77	0.87	1.00	**0.9**
Quality IC	0.80	0.72	0.77	0.67	0.73	0.75	0.85	0.72	0.80	0.89	0.75	0.68	**0.8**
Quality L	0.68	0.66	0.86	0.84	0.69	0.76	1.00	1.00	0.86	1.00	0.89	0.77	**0.8**
Regency AI	1.00	1.00	0.88	0.74	0.69	1.00	1.00	0.86	0.72	0.82	1.00	0.84	**0.9**
SIC IC	0.78	0.67	0.77	0.69	0.65	0.72	0.70	0.78	1.00	0.77	0.72	0.54	**0.7**
SIC L	0.61	0.57	1.00	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.9**
Star AC	1.00	0.85	1.00	0.78	0.90	0.78	0.74	0.89	0.72	1.00	0.95	0.72	**0.9**
Star L	0.85	0.75	0.85	0.82	0.86	0.90	0.81	1.00	1.00	1.00	1.00	1.00	**0.9**
Unique IC	1.00	0.72	0.61	0.64	1.00	0.67	0.73	1.00	0.70	0.84	1.00	0.82	**0.8**
Vanguard AC	1.00	1.00	1.00	0.75	0.74	0.80	0.72	0.92	0.74	0.83	0.81	0.77	**0.8**
Vanguard L	1.00	1.00	1.00	1.00	0.77	0.72	0.76	1.00	0.76	1.00	1.00	1.00	**0.9**
Geomean	**0.88**	**0.82**	**0.83**	**0.79**	**0.78**	**0.84**	**0.81**	**0.90**	**0.83**	**0.88**	**0.85**	**0.80**	

Equity capital

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.92	0.80	0.78	0.77	0.68	1.00	0.81	0.73	0.78	0.73	0.84	0.72	**0.79**
CDH L	0.74	0.70	0.72	0.72	1.00	0.96	0.82	0.73	0.62	0.67	0.62	0.60	**0.73**
Donewell IC	0.91	0.82	0.95	0.70	0.76	0.79	1.00	1.00	0.79	0.82	0.76	0.62	**0.82**
Donewell L	1.00	0.80	0.78	0.87	1.00	1.00	1.00	1.00	0.66	0.77	0.73	0.65	**0.84**
Enter L	0.96	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	**0.99**
Enterprise IC	0.70	1.00	0.68	1.00	0.77	0.72	0.68	1.00	1.00	1.00	0.78	0.66	**0.82**
Equity IC	0.70	1.00	1.00	0.69	1.00	0.86	1.00	1.00	0.76	1.00	0.82	0.80	**0.88**
Ghana L	1.00	0.71	0.77	0.70	0.77	0.88	1.00	0.69	0.71	1.00	1.00	1.00	**0.84**
Ghana UA	0.71	0.83	1.00	0.69	0.62	0.60	0.63	0.80	0.58	0.68	0.70	0.52	**0.69**
GhanaUnion L	0.76	0.84	1.00	0.82	0.87	1.00	0.86	1.00	0.62	1.00	0.74	1.00	**0.87**
Glico GI	1.00	0.89	0.74	0.73	0.68	0.80	0.57	0.78	0.67	0.67	0.69	0.67	**0.73**
Glico L	0.77	0.81	0.76	0.76	0.93	0.74	0.65	1.00	0.64	0.70	0.74	0.61	**0.75**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.79	**0.98**
Metropolitan IC	1.00	0.80	0.79	0.82	0.77	0.91	0.62	0.74	0.70	0.83	0.83	1.00	**0.81**
NSIA GC	0.79	0.79	0.72	0.77	0.85	0.74	0.55	1.00	1.00	1.00	0.86	0.74	**0.81**
Phoenix IC	0.79	0.90	0.89	0.79	0.74	0.91	0.65	0.85	0.71	0.96	0.99	0.72	**0.82**
Phoenix L	1.00	1.00	0.79	0.75	0.92	0.90	0.69	0.73	1.00	1.00	1.00	1.00	**0.89**
Prime I	1.00	0.86	0.68	0.65	0.54	1.00	0.52	1.00	1.00	0.97	0.71	0.66	**0.78**
Provident IC	0.65	0.71	0.77	0.68	0.68	0.71	0.71	0.92	0.73	0.76	1.00	0.99	**0.77**
Provident L	0.88	1.00	1.00	1.00	0.92	1.00	0.57	0.62	0.70	0.91	0.94	1.00	**0.86**
Quality IC	0.78	0.74	0.89	0.79	0.87	0.90	0.95	0.77	0.75	0.84	0.73	0.66	**0.80**
Quality L	0.67	0.68	0.95	0.91	0.81	0.89	1.00	1.00	0.90	1.00	0.88	0.69	**0.86**
Regency AI	1.00	1.00	0.89	0.77	0.77	1.00	1.00	0.96	0.80	0.97	1.00	0.89	**0.92**
SIC IC	0.75	0.69	0.75	0.65	0.70	0.73	0.65	0.75	1.00	0.82	0.64	0.51	**0.71**
SIC L	0.62	0.61	0.99	0.86	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.91**
Star AC	1.00	0.94	1.00	0.77	0.90	0.80	0.72	0.85	0.66	1.00	0.83	0.67	**0.84**
Star L	0.95	0.87	0.86	0.85	1.00	0.97	0.67	1.00	1.00	1.00	1.00	1.00	**0.92**
Unique IC	1.00	0.84	0.65	0.71	1.00	0.92	0.83	1.00	0.63	0.85	1.00	0.82	**0.84**
Vanguard AC	1.00	1.00	1.00	0.79	0.85	0.91	0.92	1.00	0.76	0.98	0.75	0.75	**0.89**
Vanguard L	1.00	1.00	1.00	1.00	0.94	0.86	0.85	1.00	0.71	1.00	1.00	1.00	**0.94**
Geomean	**0.86**	**0.85**	**0.85**	**0.79**	**0.83**	**0.88**	**0.78**	**0.89**	**0.78**	**0.89**	**0.84**	**0.77**	

Net premium

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.98	0.82	0.78	0.55	0.64	1.00	0.75	0.91	0.91	0.79	0.82	0.54	**0.75**
CDH L	0.65	0.69	0.67	0.58	1.00	0.98	0.97	0.75	0.60	0.71	0.50	0.55	**0.71**
Donewell IC	0.95	0.85	0.96	0.54	0.66	0.87	1.00	1.00	0.98	0.90	0.90	0.59	**0.81**
Donewell L	1.00	0.88	0.79	0.88	1.00	1.00	1.00	1.00	0.53	0.64	0.54	0.40	**0.74**
Enter L	0.99	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.97	**1.00**
Enterprise IC	0.55	1.00	0.66	1.00	0.62	0.80	0.91	1.00	1.00	1.00	0.90	0.64	**0.86**
Equity IC	0.69	1.00	1.00	0.77	1.00	0.94	1.00	1.00	0.96	1.00	0.98	0.89	**0.95**
Ghana L	1.00	0.73	0.71	0.40	0.66	0.68	1.00	0.50	0.74	1.00	1.00	1.00	**0.74**
Ghana UA	0.69	0.48	1.00	0.62	0.76	0.79	0.83	0.97	0.79	0.87	0.69	0.18	**0.67**
GhanaUnion L	0.86	0.94	1.00	0.99	0.99	1.00	0.91	1.00	0.89	1.00	0.92	1.00	**0.97**
Glico GI	1.00	0.94	0.78	0.68	0.66	0.92	0.61	0.83	0.62	0.71	0.86	0.70	**0.73**
Glico L	0.90	0.87	0.87	0.90	0.74	0.87	0.95	1.00	0.89	0.89	0.88	0.76	**0.87**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.55	**0.94**
Metropolitan IC	1.00	0.69	0.71	0.81	0.79	0.77	0.66	0.67	0.75	0.90	0.85	1.00	**0.80**
NSIA GC	0.87	0.86	0.77	0.83	0.69	0.56	0.56	1.00	1.00	1.00	0.88	0.44	**0.74**
Phoenix IC	0.85	0.92	0.90	0.71	0.77	0.90	0.86	0.96	0.85	0.98	1.00	0.80	**0.86**
Phoenix L	1.00	1.00	0.78	0.68	0.90	0.91	0.59	0.90	1.00	1.00	1.00	1.00	**0.87**
Prime I	1.00	0.88	0.54	0.28	0.44	1.00	0.34	1.00	1.00	0.99	0.66	0.44	**0.61**
Provident IC	0.65	0.65	0.76	0.44	0.63	0.74	0.97	0.60	0.94	0.81	1.00	0.97	**0.76**
Provident L	0.95	1.00	1.00	1.00	0.94	1.00	0.38	0.59	0.48	0.61	0.92	1.00	**0.73**
Quality IC	0.85	0.77	0.92	0.75	0.90	0.97	0.98	0.80	0.93	0.91	0.88	0.56	**0.84**
Quality L	0.57	0.57	0.97	0.68	0.69	0.74	1.00	1.00	0.76	1.00	0.80	0.68	**0.81**
Regency AI	1.00	1.00	0.97	0.78	0.82	1.00	1.00	0.99	0.88	0.99	1.00	0.96	**0.93**
SIC IC	0.81	0.64	0.79	0.49	0.69	0.81	0.71	0.61	1.00	0.87	0.69	0.73	**0.72**
SIC L	0.16	0.23	1.00	0.95	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.99**
Star AC	1.00	0.96	1.00	0.79	0.83	0.93	0.96	0.97	0.78	1.00	0.99	0.82	**0.89**
Star L	0.95	0.91	0.89	0.85	1.00	0.98	0.76	1.00	1.00	1.00	1.00	1.00	**0.95**
Unique IC	1.00	0.85	0.47	0.60	1.00	0.96	0.95	1.00	0.77	0.86	1.00	0.74	**0.86**
Vanguard AC	1.00	1.00	1.00	0.59	0.88	0.92	0.97	1.00	0.86	0.99	0.96	0.89	**0.89**
Vanguard L	1.00	1.00	1.00	1.00	0.94	0.89	0.90	1.00	0.76	1.00	1.00	1.00	**0.94**
Geomean	**0.83**	**0.81**	**0.84**	**0.71**	**0.81**	**0.89**	**0.82**	**0.89**	**0.84**	**0.90**	**0.87**	**0.72**	

Investment Income

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.91	0.01	0.01	0.18	0.19	1.00	0.67	0.68	0.66	0.65	0.88	0.43	**0.24**
CDH L	0.01	0.02	0.02	0.28	1.00	0.94	0.81	0.43	0.12	0.20	0.22	0.29	**0.21**
Donewell IC	0.01	0.27	0.11	0.28	0.31	0.50	1.00	1.00	0.57	0.63	0.56	0.44	**0.44**
Donewell L	1.00	0.12	0.04	0.36	1.00	1.00	1.00	1.00	0.74	0.84	0.67	0.25	**0.46**
Enter L	0.48	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.96	**1.00**
Enterprise IC	0.03	1.00	0.01	1.00	0.20	0.48	0.58	1.00	1.00	1.00	0.52	0.58	**0.45**
Equity IC	0.03	1.00	1.00	0.30	1.00	0.52	1.00	1.00	0.49	1.00	0.60	0.57	**0.72**
Ghana L	1.00	0.10	0.07	0.25	0.42	0.58	1.00	0.75	0.67	1.00	1.00	1.00	**0.46**
Ghana UA	0.05	0.23	1.00	0.22	0.75	0.22	0.75	0.84	0.33	0.37	0.20	0.13	**0.37**
GhanaUnion L	0.11	0.55	1.00	0.99	1.00	1.00	0.85	1.00	0.73	1.00	0.72	1.00	**0.88**
Glico GI	1.00	0.11	0.03	0.18	0.28	0.37	0.49	0.31	0.22	0.35	0.43	0.34	**0.23**
Glico L	0.05	0.21	0.05	0.49	0.89	0.40	0.75	1.00	0.26	0.42	0.34	0.47	**0.38**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.95	**1.00**
Metropolitan IC	1.00	0.11	0.09	0.21	0.39	0.56	0.49	0.50	0.45	0.71	0.66	1.00	**0.38**
NSIA GC	0.04	0.08	0.05	0.59	0.81	0.44	0.54	1.00	1.00	1.00	0.97	0.76	**0.48**
Phoenix IC	0.02	0.10	0.05	0.16	0.24	0.55	0.73	0.77	0.74	0.97	0.39	0.67	**0.35**
Phoenix L	1.00	1.00	0.03	0.31	0.65	0.80	0.47	0.88	1.00	1.00	1.00	1.00	**0.57**
Prime I	1.00	0.03	0.01	0.03	0.78	1.00	0.21	1.00	1.00	0.87	0.56	0.51	**0.24**
Provident IC	0.47	0.02	0.01	0.06	0.13	0.24	0.94	0.90	0.80	0.81	1.00	0.30	**0.22**
Provident L	0.25	1.00	1.00	1.00	0.87	1.00	0.68	0.89	0.77	0.96	0.93	1.00	**0.91**
Quality IC	0.02	0.05	0.06	0.34	0.19	0.26	0.43	0.17	0.47	0.77	0.70	0.59	**0.27**
Quality L	0.04	0.17	0.30	0.83	0.74	0.90	1.00	1.00	0.98	1.00	0.91	0.72	**0.69**
Regency AI	1.00	1.00	0.09	0.14	0.34	1.00	1.00	0.56	0.37	0.69	1.00	0.65	**0.49**
SIC IC	0.01	0.01	0.01	0.07	0.30	0.30	0.44	0.40	1.00	0.53	0.27	0.52	**0.19**
SIC L	0.08	0.24	0.75	0.64	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.82**
Star AC	1.00	0.10	1.00	0.37	0.69	0.45	0.84	0.94	0.81	1.00	0.97	0.53	**0.61**
Star L	0.55	0.16	0.15	0.61	0.90	0.76	0.70	1.00	1.00	1.00	1.00	1.00	**0.64**
Unique IC	1.00	0.05	0.02	0.06	1.00	0.44	0.81	1.00	0.69	0.95	1.00	0.84	**0.36**
Vanguard AC	1.00	1.00	1.00	0.26	0.28	0.51	0.58	0.73	0.48	0.58	0.24	0.11	**0.44**
Vanguard L	1.00	1.00	1.00	1.00	0.89	0.74	0.55	1.00	0.30	1.00	1.00	1.00	**0.82**
Geomean	**0.19**	**0.17**	**0.11**	**0.31**	**0.54**	**0.60**	**0.70**	**0.77**	**0.61**	**0.76**	**0.65**	**0.57**	

Claims

INSURERS	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Geomean
Activa I	0.82	0.71	0.81	0.76	0.72	1.00	0.91	0.83	0.91	0.80	0.96	0.76	**0.83**
CDH L	0.73	0.68	0.73	0.75	1.00	0.98	0.97	0.77	0.68	0.70	0.66	0.63	**0.76**
Donewell IC	0.93	0.76	0.92	0.73	0.66	0.85	1.00	1.00	0.97	0.84	0.88	0.67	**0.84**
Donewell L	1.00	0.85	0.76	0.88	1.00	1.00	1.00	1.00	0.76	0.82	0.78	0.68	**0.87**
Enter L	0.94	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.94	**0.99**
Enterprise IC	0.74	1.00	0.72	1.00	0.79	0.81	0.70	1.00	1.00	1.00	0.90	0.70	**0.85**
Equity IC	0.74	1.00	1.00	0.82	1.00	0.92	1.00	1.00	0.96	1.00	0.96	0.85	**0.93**
Ghana L	1.00	0.70	0.71	0.68	0.69	0.84	1.00	0.79	0.79	1.00	1.00	1.00	**0.84**
Ghana UA	0.71	0.83	1.00	0.71	0.82	0.80	0.88	0.85	0.80	0.81	0.81	0.54	**0.79**
GhanaUnion L	0.84	0.86	1.00	0.99	0.98	1.00	0.91	1.00	0.88	1.00	0.91	1.00	**0.95**
Glico GI	1.00	0.90	0.80	0.73	0.72	0.91	0.72	0.76	0.69	0.70	0.85	0.71	**0.78**
Glico L	0.84	0.88	0.83	0.77	0.95	0.82	0.72	1.00	0.72	0.84	0.88	0.64	**0.82**
Met L	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	0.76	**0.98**
Metropolitan IC	1.00	0.81	0.82	0.80	0.75	0.89	0.74	0.77	0.78	0.85	0.77	1.00	**0.83**
NSIA GC	0.86	0.77	0.82	0.82	0.92	0.72	0.72	1.00	1.00	1.00	0.98	0.80	**0.86**
Phoenix IC	0.83	0.84	0.89	0.78	0.79	0.88	0.88	0.90	0.85	0.98	1.00	0.75	**0.86**
Phoenix L	1.00	1.00	0.73	0.70	0.80	0.78	0.73	0.86	1.00	1.00	1.00	1.00	**0.87**
Prime I	1.00	0.75	0.72	0.64	0.82	1.00	0.61	1.00	1.00	0.97	0.86	0.69	**0.82**
Provident IC	0.75	0.68	0.80	0.67	0.69	0.73	0.98	0.97	0.93	0.84	1.00	0.99	**0.83**
Provident L	0.85	1.00	1.00	1.00	0.91	1.00	0.70	0.88	0.79	0.95	0.91	1.00	**0.91**
Quality IC	0.83	0.71	0.86	0.81	0.85	0.95	0.98	0.80	0.91	0.85	0.88	0.71	**0.84**
Quality L	0.69	0.67	0.93	0.90	0.79	0.83	1.00	1.00	0.97	1.00	0.88	0.74	**0.86**
Regency AI	1.00	1.00	0.96	0.78	0.82	1.00	1.00	0.95	0.88	0.98	1.00	0.78	**0.92**
SIC IC	0.80	0.68	0.80	0.71	0.74	0.78	0.79	0.79	1.00	0.81	0.85	0.79	**0.79**
SIC L	0.61	0.58	0.99	0.77	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	**0.90**
Star AC	1.00	0.90	1.00	0.80	0.97	0.90	0.96	0.95	0.82	1.00	0.99	0.74	**0.92**
Star L	0.88	0.83	0.83	0.74	0.92	0.85	0.73	1.00	1.00	1.00	1.00	1.00	**0.89**
Unique IC	1.00	0.73	0.65	0.74	1.00	0.94	0.96	1.00	0.80	0.95	1.00	0.40	**0.82**
Vanguard AC	1.00	1.00	1.00	0.74	0.83	0.91	0.81	1.00	0.86	0.98	0.95	0.77	**0.90**
Vanguard L	1.00	1.00	1.00	1.00	0.83	0.76	0.88	1.00	0.79	1.00	1.00	1.00	**0.93**
Geomean	**0.87**	**0.83**	**0.86**	**0.80**	**0.85**	**0.89**	**0.87**	**0.92**	**0.88**	**0.92**	**0.92**	**0.79**	